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Air Superiority at Red Flag

Mass, Technology, and Winning the Next War

Joseph W. Locke
Lieutenant Colonel, USAF

AIR UNIVERSITY

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Air Superiority at Red Flag

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Foreword

Soviet premier Joseph Stalin once famously noted, "Quantity has a quality all its own." Certainly the Allied victory in the Second World War, in which Stalin's war machine played a vital role, depended on the tremendous output from Allied armaments factories that swamped Nazi Germany and imperial Japan. Yet studies of air warfare have always emphasized the important role of technological quality, as opposed to simple mass. Certainly Stalin's much larger air force was overwhelmed in June 1941 by the technologically superior and better-trained Luftwaffe. North Atlantic Treaty Organization planners in the 1970s and the 1980s likewise sought to check Warsaw Pact numerical superiority by fielding smaller numbers of superior aircraft.

Yet planners would be unwise to neglect the importance of "mass" even in today's high-tech air superiority environment. Lt Col Joseph W. Locke's study offers a model for understanding the relationship between technology, mass, and attrition in aerial warfare that is useful for shaping operational and strategic force decision making. The F-15C's offensive counterair (OCA) sweep mission within the capstone United States Air Force exercise Red Flag highlights one potentially useful relationship that has value as a model for air superiority. A rigorous comparison of data from 299 Red Flag missions suggests a change in attrition rates that correlates with force ratios. The most significant implication of this study, however, is the predicted variance in changing kill ratio as the force ratio changes. The wide middle area of stability, identified as numerical attrition, is consistent with the traditional notion that kill ratio is largely a function of training and technology. It is also consistent with most of the historical record, including the early campaigns of World War II, that suggested that nominal changes in the relative mass of forces brought about little change in the kill ratio. This is also the reason evolving technology often produced the only observable change in the kill ratio. The rapid change in attrition rate at either end of the model also has great explanatory value. By indicating regions where disproportionate force dictates a similarly lopsided victory, the concept accounts for several notable historical cases, such as Operations Desert Storm (1991) and Allied Force (1999). With continuous devel-

opment and the incorporation of additional data, these diagrams can aid operational planners in developing more effective air superiority campaigns in future conflicts.

"Air Superiority at Red Flag" was originally written as a master's thesis for Air University's School of Advanced Air and Space Studies (SAASS) at Maxwell AFB, Alabama. The thesis was directed by Lt Col John Terino, a member of the SAASS faculty. Lieutenant Colonel Locke's thesis is thoroughly researched, analytically rigorous, and forcefully written. It was the recipient of the 2008 "SAASS Thesis Award in Technology, Space, and Cyberspace," sponsored by the Air University Foundation. SAASS is pleased to partner with the Air Force Research Institute and Air University Press to publish it as a Drew Paper, thereby making it available to a wider audience.

RICHARD R. MULLER
Professor of Military History and Associate Dean
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About the Author

Lt Col Joseph W. Locke graduated from the United States Air Force Academy in 1995. After completing undergraduate pilot training in 1997, he proceeded to fly F-16CJs at Mountain Home Air Force Base (AFB), Idaho. Subsequently, Colonel Locke served as an air liaison officer and joint terminal air controller from 2001 to 2003 and supported several units, including the 10th Mountain Division, Operations Detachment Alpha 365 and 1st Battalion 5th Special Forces Group in both Operations Enduring Freedom and Iraqi Freedom. He returned to the F-16CJ in 2003 and served as an instructor pilot, flight commander, and assistant director of operations at Spangdahlem Air Base, Germany. He is a senior pilot with 1,500 hours of flying. Colonel Locke graduated from the Air Command and Staff College and SAASS.

Colonel Locke, a native of Cedaredge, Colorado, is married to the former Erin M. O'Connell of Evanston, Wyoming. They have three children: Caron, Jessica, and Garrett.

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The other major hurdle in this thesis was my own rudimentary understanding of computers and statistics. Capt Travis Herbranson personally saved me many hours of work by assembling the final database and checking it for accuracy. In addition, Dr. Melanie Teichert and Dr. Gary Schaub helped me through the doldrums of statistics to find patterns in the chaos.

I cannot say enough about the love and support I received from my wife and other family members. Their enthusiasm and understanding made the past year a pleasure instead of a year of pain.

Introduction

Through nearly 2,500 years of recorded warfare, the strategic debate over the primacy of quantity versus quality remains undecided. Esoteric examples of highly trained and motivated soldiers defeating massive, yet impotent, hordes clutter history. Hannibal's exploits at Cannae, Napoléon's victory at Austerlitz, and Nelson's victory at Trafalgar are only a few examples of great captains overcoming the odds and defeating numerically superior forces with skill and guile. Military historians often cite these victories and analyze them for insight and inspiration. With so many examples for inspiration, however, it is easy to forget that, in many cases, mass wins. Many skilled commanders have fallen to the weight of superior numbers despite heroic efforts and battlefield genius. Therefore, the essential issue for commanders is not about quality or quantity. Instead, commanders must focus on how these two factors interact and what combination provides the best chance for victory.

Clausewitz understood this interaction and combined these complementary factors into a unifying concept of strength. Strength combines raw numbers with a host of other factors—including training, tactics, skill, weapons, initiative, and commander's genius—that routinely affect the fighting strength of the opposing armies and their soldiers.[1] Qualitative differences involving these factors can create advantages that offset numerical shortcomings, especially when applied at decisive points. At the strategic and operational levels of war, the challenge is to determine the strength required for a desired effect. Attacking with insufficient strength ensures the loss of offensive power at the expense of achieving the desired objective. Conversely, using excessive strength squanders effort better used to exploit opportunities concurrent with the main attack or useful in influencing the attainment of other objectives.

Operations Desert Storm and Allied Force and the opening gambit of Operation Iraqi Freedom are routinely invoked as contemporary benchmarks of American conventional military accomplishment. Although the skill required to execute each of the previously mentioned campaigns was noteworthy, the United States' disproportionate strength heavily favored American military victory. In each case, the strategic environment held the

enemy completely at risk, while at the same time ensuring American and allied forces were immune from attack. Col John Warden describes this situation as Case II-offensive operations.[2] He fittingly describes this situation as a "commander's dream . . . [that] provides the opportunity for decisive action—action so decisive the war can theoretically be won from the air."[3] As a result, his famed five-ring model was well suited for the situation where United States (US) Air Force stealth platforms and precision munitions could combine to attrite enemy capability without a direct ground confrontation. Regrettably, visions of brief, pristine conflicts with only minuscule losses have transformed recent strategic opinion toward a belief that such victories were not only possible but also probable. According to some, high-technology war made victory such a foregone conclusion that visionaries were primarily concerned with refining the elegance of the final product. Obviously, the recent lessons from Iraq and Afghanistan highlight the fallacy that tactical capability ordains strategic victory. As America focuses toward winning the war against terror, the temptation is for the United States to rest on its laurels in the conventional arena.

Frederick Kagan highlights the pitfalls of believing "future adversaries will simply cede the realm of conventional war to the US."[4] He suggests America's aerial hegemony is a temporary phenomenon that will last only until other nations find methods of incorporating or countering its technology. America's enemies will adapt for their own survival and attempt to alter the balance of power in their favor. The first step in the process, developing counter tactics, is easily identifiable in the conflicts since Desert Storm. Serbian surface-to-air missiles (SAM) operators successfully shot down a stealthy F-117 using an outdated SA-3, ingenuity, and patience.[5] Insurgent groups in Iraq and Afghanistan are dispersing and blending into the terrain to negate the advantage of American high-technology reconnaissance and precision-strike capabilities. Other nations are actively taking the steps necessary to counter American technology directly by developing their own innovative, high-technology systems to hold American aerial hegemony at risk.

In the future, when American forces act outside of Warden's Case II scenario, immaculate victory becomes less likely, and the stakes increase dramatically, yet victory remains the only option.

In that case, the depth of America's military strength becomes more influential than its esoteric application. This realization does not negate the great strides evident in such new planning methods as effects-based operations or systemic operational design.[6] Understanding the enemy, the enemy's centers of gravity, and potential weaknesses are always critical elements in any viable plan no matter the scenario. The main difference is in execution. Where enemy offensive strength is considerable, American offensive potential diminishes due to increases in defensive requirements. Conversely, when enemy defensive strength is significant enough to prevent—at least temporarily—strategic attacks on their centers of gravity; tactical military force-on-force confrontation is the only remaining option.

Before the next major war begins, strategic decisions about military force structure will shape the feasibility of operational plans and preordain the costs in both dollars and lives required for victory. The increasing expense of next generation aerial weapons means that current and future inventories are shrinking at an alarming rate. Current trends suggest that 20 B-2s and fewer than 200 F-22s will face the responsibility of defending America's shores and projecting power worldwide. Future systems, like the joint strike fighter, will similarly supplant current aircraft with increased capabilities and reduced numbers. These shrinking inventories of high-technology aircraft will likely result in a future conflict where America will fight outnumbered and be completely reliant on technology to maintain a preponderance of Clausewitzian strength. Therefore, efficiency is essential to maintain freedom of action.

Efficiency is only attainable through understanding. By exploring the relationship between mass and technology in the broader context of aerial combat, commanders can increase the quality of their operational and strategic decisions before placing forces in harm's way. How much mass is needed to accomplish the objective? Will more aircraft increase the chances of success? If more aircraft will help, how much of an advantage will accrue? What are the potential effects of a new technology on the battlefield? Bounding these operational questions are strategic decisions about numbers and types of aircraft made years or even decades before a confrontation erupts.

Finding a method for understanding these relationships is essential for enhancing the decision process.

Purpose and Objectives

This study proposes a model for understanding the relationship between technology, mass, and attrition in aerial warfare that is useful for shaping operational and strategic-force decision processes. Red Flag serves as the data set used to highlight and explain one potentially useful relationship. This daunting task, if taken as a whole, could lead to an unusable mess confused by the limits of training and result in sweeping generalities irrelevant to strategic and operational users. Additionally, like most exploratory studies attempting to use observed data from events designed for another purpose, this complex scenario contains numerous unaccounted for variables that hamper pristine scientific correlation.[7] Instead, by focusing the analysis on a narrow piece of the larger whole, relationships become less ambiguous, trends become clearer, and correlation more direct. The ideal subject for analysis includes as few training limitations as possible, maintains the greatest possible interaction with the adversary forces, shows a consistent level of participation and performance over time, and represents one of the emphasized mission areas exercised during Red Flag. Therefore, the air-to-air mission area, and specifically the F-15C and the offensive counterair-sweep mission, provides an ideal center of attention.[8]

Air superiority is the "pivotal prerequisite for success" that enables every other airpower function from strategic attack to airlift.[9] As such, it is a critical capability with grave strategic implications for failure. Once air superiority is established, the US Air Force can directly focus on attacking the enemy's ability and will to fight. Without it, however, every mission becomes a fight for the air itself and results in little pressure applied to the enemy. While air superiority in and of itself does not guarantee victory, it helps to ensure a joint force commander's freedom of maneuver and initiative within his operational area. This lesson, reinforced in every major operation since World War I, requires constant focus and is easy to take for granted.

Chapter 1 highlights the quest for a more complete understanding about the character of aerial combat and explains the limitations of the major approaches applied in this quest. Chapter 2 examines Red Flag and statistically explores the Red Flag data to create an attrition model relating mass and technology. This section helps those uninitiated with the Red Flag exercise and those interested in the underlying explanation of the final relationships. Readers familiar with Red Flag or uninterested in the statistical data analysis can skip to chapter 3 to enter directly into the exploration of the results of the analysis and its implications.

Chapter 3 develops and recommends a method of attrition modeling designed to help commanders make informed decisions about air strategy at the operational level of war. It attempts to account for the character of modern aerial combat, is flexible enough to adjust to the realities of different scenarios, and is simple enough for timely results to shape campaign plans. Chapter 4 analyzes the strategic implications of the data and makes recommendations for additional research.

Notes

(Notes for this chapter and the following chapters appear in shortened form. For full details, see appropriate entries in the bibliography.)

1. Clausewitz, *On War*, 194–97.
2. Warden, *Air Campaign*, 17. Warden identifies five specific cases of air superiority characterized by the vulnerability of blue and red airfield/rear areas and the accessibility of the battle-lines to aircraft. Case I (the Chess Game) holds both sides vulnerable across all three variables. Case II (Offense) threatens red and holds blue immune to attack. Case III (Defense) is the opposite of Case II. Case IV (Limited Options) occurs when both sides are immune from attack on their resources but can fight over the battle area. Finally, Case V is a scenario where neither the battlefield nor the adversary homelands are vulnerable to aircraft.
3. Ibid., 33.
4. Kagan, *Finding the Target*, 390.
5. Lambeth, *NATO's Air War for Kosovo*, 117–18.
6. Air Force Doctrine Document (AFDD) 2.0, *Operations and Organization*, 13–20, 85–97; and Schmitt, "Systemic Operational Design," unpublished paper.
7. Kutner, Nachtsheim, and Neter, *Applied Linear Regression Models*, 345–46.
8. AFDD 2–1.1, *Counterair Operations*, 17.
9. AFDD 1, *Air Force Basic Doctrine*, 41.

Chapter 1

Review of Literature

The object of science is knowledge; the object of art is creative ability.

—Carl von Clausewitz
On War

Like war as a whole, airpower theory has evolved with an acknowledgment that strategy is both an art and a science. Controversy between these two diametric terms stems from the faulty belief that success lies in emphasizing one over the other. The variable character of warfare and the unique temperament of individual battles ensure the irrelevance of either a checklist methodology or blind trust in a previously successful commander. War is fickle if for no other reason than because it is a clash of wills between learning and evolving opponents.[1] Effective strategy then must balance both the knowledge of what is probable with the *coup d'oeil* to realize what is possible. Unfortunately, extrapolating tactical science to help shape operational and strategic art is difficult.

Such land warfare maxims as successful attacks needing a three-to-one advantage provide commanders with a baseline for gauging the strengths of their plan. The rule, however, remains open for interpretation within the specific context of the situation. Environmental factors like terrain and vegetation present unique challenges and opportunities that focus on a commander's perception of the possible.[2] Similarly, the human element is an overriding force in land warfare that greatly influences a commander's options.[3] The machines used to augment human power often magnify the effects of the human will. Mechanized troops that are out of fuel can regress to a role as infantry to continue the fight. Admittedly, their effectiveness will decrease, but as long as their will remains, resistance will continue.

Unlike ground combat, however, aerial warfare exists in a different environment and follows a different set of rules. The aerial environment is largely uniform and unpredictable. When Airmen confront each other in the sky, few geographic benefits

provide an initial edge. There is no terrain to supply an advantage or vegetation to offer concealment. Weather can obviously play a role, but its effects are often equally restrictive for both sides. The sun may offer a fleeting advantage in the visual engagement, but only for an instant. Admittedly, geography exerts an influence on basing and determines flight routes and proximity to the battle. However, global reach technology makes virtually any location accessible with the right equipment. As a result, the balance of technology between the opposing forces defines the realm of the possible in aerial warfare. Lt Col William Sherman eloquently explains this relationship in his 1926 book, *Air Warfare*, by suggesting, "The man in the air is peculiarly at the mercy of material things. No matter how great his determination nor how high his courage, he is helpless against an enemy with a machine that can out-run, out-climb, and out-maneuver him."[4] Additionally, an aircraft out of fuel or weapons must either retreat to safety or perish. The Airman in combat is completely reliant on his machine for relevance on the battlefield. Technology, like terrain, however, can only go so far in determining the outcome of conflict. Pilot training, tactics, numbers of aircraft, and chance all play into the relationship to determine the outcome. This is true historically and will continue to be true into the near future.

The Combined Bomber Offensive

One germane historical example is the combined bomber offensive of World War II, since it provides an excellent case to highlight the aforementioned interaction of factors. Changes in relative levels of technology and mass between the Allied and Axis powers resulted in vastly different outcomes in the skies over Germany. Largely understood as a war of attrition, the air war's character and levels of losses evolved greatly between when the US Army Air Forces (AAF) entered the war in 1942 and final victory in 1945. Early air-to-air combat against the Germans in 1942 resulted in an even kill ratio of approximately 1:1.[5] Given the high level of German experience in the air-to-air arena compared to the green American pilots, it is fortunate that results were not worse. Additionally, with the stress on unescorted bombing in 1942, the AAF put little emphasis on

the air superiority role. By 1943, however, the need for fighter escort was obvious, and fighter sortie counts began to rise. For the first several months, force ratios between the fighters remained about even, but by early 1944, the Allies had nearly a three-to-one advantage in fighters over the intercepting German aircraft.[6] Initially, this had little effect on the kill ratio. Between 6 April and 5 June 1944, the Allies flew nearly three times as many air-to-air sorties as the Germans but accounted for a kill ratio of only 1.2:1.[7] The following three-month period, however, saw a twofold increase in Allied forces that significantly altered the balance of power. Between 6 June and 5 September 1944, Allied fighter sorties outpaced the German missions sixfold, and the fighter kill ratio jumped to 6.8:1.[8]

Pilot training and new technology explain some of this dramatic jump in kill ratio. A lack of German emphasis on producing pilots early in the war resulted in a dramatic decrease in their pilot's experience and training levels by 1944.[9] A United States Strategic Bombing Survey (USSBS) document, however, contradicts this interpretation. While it acknowledges that overall bomber losses were declining, it concludes that the number of "bombers lost to E/A [enemy aircraft] per 100 combats with E/A" increased from 5.0 in late 1943 to a high of 17.7 in the second quarter of 1944.[10] While increases in the effectiveness of German armament account for some of this increase, it would not be possible without a high degree of pilot skill.[11] Similarly, many sources credit the introduction of the P-51 Mustang in late 1943 with tipping the technological advantage toward the Allies.[12] The Mustang, however, provided 24 percent of the Allied fighter sorties between 6 April and 5 June 1944 and 30 percent between 6 June and 5 September 1944. Again, this small change can account for some of the difference in the kill ratio, but it cannot explain the dramatic change in kill ratio from about even to an advantage of 6.8:1 in only three months. Morale could also have played a part, but the German war machine continued to function for more than a year after the Normandy invasion. Instead, the dramatic increase in the mass of the Allied air offensive seems to correlate most closely with the increase in the kill ratio. Noting this trend, Edward Luttwak concludes that Germany's "qualitative military superiority had become insufficient to offset numerical inferiority."[13]

Air Force Doctrine Document (AFDD) 1, *Air Force Basic Doctrine*, states, "The purpose of mass is to concentrate the effect of combat power at the most advantageous place and time to achieve decisive results . . . through effectiveness of attack, not just overwhelming numbers."[14] Given airpower's inherent speed, range, and flexibility, this concept is potentially more valid today than ever before. Whether measuring numbers of aircraft or the number of targets each aircraft can attack, however, both are merely tactical measures, which require expansion. Endurance, sortie generation, and industrial potential are all important measures of mass at the operational and strategic level.

Unlike land warfare, where combat assets—man or material—can remain within the confines of battle from the start of an operation to the decision, combat aircraft effectiveness is fundamentally limited by time. Fuel becomes a significant problem during an engagement as fuel consumption rates increase. Aircraft unable to remove themselves from the fight before running out of fuel become unnecessary casualties aiding the enemy's cause. Likewise, opportunities to press an advantage may slip away if fuel restricts pursuit. Similarly, weapons capacity and use rates have virtually the same effect. An aircraft out of munitions becomes a liability rather than an asset in combat. Aerial refueling goes a long way to solving part of the problem by allowing aircraft to extend their range from home base, but fuel consumption remains an issue for deciding the duration combat aircraft can remain engaged. Weapons consumption, however, is only resolved by returning to base. As a result, harmonizing the time an aircraft needs to remain in combat with the rate it expends fuel and munitions is a delicate balance. Expect too much and the operational plan begins to break apart with gaps in capability. Expect too little and the sorties are wasted through inefficiency.

Closely nested with the on-station time requirement, sortie-generation capability is essential to keeping aircraft actively in the fight. Two of the most important measures of this capability are utilization (UTE) rates and average sortie duration (ASD). The UTE rate measures the average number of sorties an individual aircraft is required to fly in a specific period to accomplish the tasking.[15] ASD simply averages the amount of time individual sorties remain airborne.[16] Increasing either measure

puts added strain on the aircraft and maintenance. Ground turn times also can affect the overall measure of mass, because the longer aircraft are unavailable between sorties results in decreasing UTE rates. Up to a point, generating more sorties will increase the efficiency of the operation and ensure maximum pressure on the enemy. Past that point, however, efficiency rapidly decreases as aircraft begin to break faster than ground crews can make repairs. Therefore, a balanced operational plan must account for these realities and attempt to use aircraft at, but not exceeding, their maximum efficiency.

The last measure of mass is usually unaccounted for until it is too late. Manufacturing aircraft is a long process that requires specialized facilities and specially trained workers. Therefore, underestimating the number of aircraft required can have catastrophic consequences. Again, the German experience in World War II proves instructive. As German lessons from the Spanish Civil War indicated, "The problem of air superiority was not primarily one of numerical strength but of the quality of the personnel and weapons in the [air] arm."[17] After spectacular victories in Poland and France in 1939–40, the German government did not increase aircraft production to prepare for the larger battles ahead.[18] Instead, "the Germans were sure that their technological expertise and military competence could master any threat."[19] By the time the Luftwaffe realized the error, it was too late to increase aircraft production enough to stem the tide of Allied numerical superiority.[20]

By contrast, Pres. Franklin D. Roosevelt set the goal of producing 10,000 combat aircraft a year in November 1938 and increased the goal to 50,000 a year in May 1940.[21] Despite the foresight, American industry was unable to make the transition rapidly. Production rates reached the 10,000 aircraft a year mark in early 1942 and did not exceed 50,000 a year until 1943.[22] Given the significantly longer lead times to produce modern high-technology military aircraft, the timeline to increase the size of today's Air Force would likely be significantly longer.[23] Today's trend toward shrinking aircraft inventories and long production lines accentuates this dilemma. Unlike the preparation for World War II, modern combat aircraft have virtually nothing in common with automotive or even civilian aircraft production. No longer can automobile factories and

their workers simply transition from building Fords to building F-22s. Instead, special facilities and specialized workers with the skills to work titanium, carbon fiber, and a myriad of other specialized materials would have to be grown.

Combining that production ramp-up timeline with the lethality of current systems means the US Air Force will likely have to fight and win the next war with the equipment it has on hand. Therefore, understanding the combat repercussions of peacetime force structure is essential to determining future American wartime success. With the increased lethality of forces, however, the time to wait and see what happens may be minimal. Generals will face a rapid succession of events where choices about when and where to mass forces can rapidly escalate towards inevitable victory or defeat before new aircraft production becomes a reality. Underestimating the number of aircraft required to gain and maintain air superiority against a well-equipped enemy may prove unrecoverable in an unexpected war. Overestimating, however, is no longer fiscally feasible.

Therefore, attempting to understand the relationship between mass and technology is essential for intelligent force structure decisions. Similarly, understanding the relationship could prove helpful for building successful operational plans. Finding a method to extrapolate tactical relationships into a useful form for shaping operational and strategic plans, however, has proven elusive. The past century witnessed several different methods for estimating the effort and time required to establish air superiority. Ranging from simple historical extrapolation to complex computer models, these techniques attempt to inform a commander's decisions with varying degrees of success.

Mathematical Modeling

F. W. Lanchester published one of the first models for aerial warfare in his 1916 book, *Aircraft in Warfare*. One of the earliest attempts to write a coherent airpower theory, he envisioned the full range of missions from reconnaissance to strategic attack and argued for the necessity of an independent air arm to maintain air superiority over enemy forces.[24] Despite his significant contributions and balanced analysis of early airpower, Lanchester's standing among aviators faded in comparison to

less mathematically inclined theorists such as Giulio Douhet and William "Billy" Mitchell in the 1920s. Despite his obscurity to the line Airman, he had a deep and persistent influence in the emerging field of operations research.

Intertwined within Lanchester's analysis of airpower was a deterministic mathematical relationship for analyzing military forces. Deterministic methods use equations to describe a relationship between relevant, quantifiable variables. As a result, they provide predictable and repeatable answers to known questions. They are extremely useful in the regime of pure science where an input directly correlates to a known effect. Unfortunately, if the analysis is biased or skewed in sections of the relationship, erroneous results can lead to poor decisions.[25] Lanchester's most prominent and controversial equation is the N-squared law that uses differential equations to derive a simple mathematical relationship to assess the strength of technologically driven military forces on the battlefield. His N-squared law suggests that "the fighting strengths of a force may be broadly defined as proportional to the square of its numerical strength multiplied by the fighting values of its individual units."[26] The derivation of the equation is unimportant in this analysis except to explain that Lanchester's measure of military strength equals the force's quality (M) times the square of its mass (b) as expressed by the equation:

$$\mathit{Strength} = Mb^2$$

Assuming an accurate quality factor (M) for each side, the model provides a deterministic method of estimating the winning side and the timeline for the decision based on the interaction of quality and raw numbers.[27] J. F. C. Fuller even used the N-squared law as part of the rationalization to emphasize battlefield technology over mass.[28] Unfortunately, the appealing simplicity masks the complexity and variability of actual combat. By ignoring factors like morale, combined arms, and movement, Lanchester's equation requires significant modification to produce acceptable levels of accuracy.[29] Additionally, even with modification, the factors need specific "tuning of the equations" for the results to match historical examples.[30] As a result, Kenneth Watman, currently the deputy chief of staff for strategic plans and programs at Headquarters Air Force, con-

cludes, "It cannot be said that the Lanchester equations have ever constituted a generalizable model of warfare."[31]

Recognizing the deficiencies of Lanchester, Col Trevor N. Dupuy, US Army, attempted to predict future battlefield results through a rigorous quantitative analysis of military engagements throughout history. Approaching the problem from an entirely different direction, his quantified judgment method of analysis (QJMA) used 73 discrete variables, including mass, technology, the environment, surprise, morale, and other intangible factors to calculate a "power potential ratio."[32] All told, his methodology enables the deterministic calculation of a winner and the approximate number of casualties on both sides. To bolster his methodology, he concludes that his results are similar to Lanchester's despite the differing methods.[33] Dupuy's methodology, however, never reached acceptance as a viable methodology, and the QJMA model had little lasting effect on modern modeling practice.

Instead, other methods of predicting combat outcomes proved more feasible. Joshua Epstein made a substantive addition to the field with the creation of the adaptive dynamic model that accounts for some of the many shortcomings omitted by Lanchester, including unit maneuvers and diminishing marginal returns on increased force sizes (tactical over-crowding).[34] His model gained some credibility and helped to shape the debate about force postures late in the Cold War. Unfortunately, as Steven Biddle has pointed out, his model shares one weakness with Lanchester's model because it "displays unstable equilibrium behavior."[35] Deterministic calculation induces the flaw by ignoring the realm of chance. As a result, when opposing forces are closely matched, minuscule changes in a single input variable can result in large differences in the outcome.

Contrasting with the exact answers of deterministic models, stochastic models use similar equations but use statistical variability to influence the model's output.[36] These models rely on randomness and repeated calculations to create a solution indicating both the needed answer and a perspective on the variability in the solution.[37] As a result, they can account for problems with deterministic models and their unstable equilibrium behaviors. The drawback is they require a great deal of computing power. The remarkable leaps in computer tech-

nology over the past half century enabled the rapid growth of stochastic computation and modeling. In turn, these stochastic computer models are facilitating a robust analysis program within the Department of Defense (DOD).[38]

Ranging from specific tactical analysis to broad strategic simulation, current computer war-gaming techniques offer the potential for enlightening operational strategy. Several technical models, like the trajectory analysis program, provide detailed analyses of air weapon kinematics and lethality that actively shape the development of aerial tactics, techniques, and procedures.[39] On the other end of the spectrum, strategic simulations integrate seamlessly in large-scale war games that help leaders refine their strategic thinking.[40] Modern modeling and simulation techniques also have the potential to shape operational plans.

Planning Operation Desert Storm

During planning for Operation Desert Storm, staffs attempted to estimate aerial attrition for the upcoming campaign. The Air Staff's Checkmate Doctrine Division produced an early effort, dated 27 August 1990. It used a combination of "quantitative analysis, historical experience, and sound professional judgment to derive a reasonable estimate of projected aggregate losses."[41] Models developed for a conflict against the Soviets resulted in an estimate of 2 percent attrition. Adding depth to the analysis, they used Operation Linebacker II as a historical model with an overall attrition rate of 1.4 percent. By comparing relevant technological and political factors, the division concluded that an overall attrition rate of between 1 to 2 percent was likely and would result in the loss of 20 to 40 aircraft in the first six days of aerial operations. Unfortunately, it provided no insight regarding which types of aircraft were vulnerable or the reason for their calculated vulnerability.

A later analysis, dated 12 December 1990, by the secretary of defense's Program Analysis and Evaluation Division used a similar but more in-depth methodology that divided attrition rates into four combat categories: air-to-air, interdiction, close air support, and multirole. Using an estimation of 50,000 total sorties resulted in anticipated total losses of 210 fighters, in-

cluding 14 from air-to-air engagements, 71 from interdiction, 88 from close air support, and an additional 36 losses of multirole aircraft.[42] This was obviously not far from the actual Operation Desert Storm tally of 65,000 sorties but a gross overestimation of the actual 38 aircraft losses.[43] Additionally, with an expected campaignwide combat attrition rate of 0.42 percent, this estimate appears executable. Unfortunately, it focused exclusively at the strategic level of war and made little effort at analyzing the operational implications of the prediction.

Taking a closer look at the projected losses compared to the number of aircraft deployed paints a different picture. Using Gulf War Air Power Survey figures for the number of deployed aircraft, 210 losses would equal 15 percent of the coalition fighter and bomber force destroyed.[44] A more detailed breakout indicates projected aircraft loss percentages would equal 7 percent of air-to-air, 27 percent of interdiction, 39 percent of close air support, and 9 percent of multirole aircraft.[45] The estimate also includes 623 "additional battle damage incidents," which suggests that 60 percent of coalition aircraft would either be destroyed or damaged in combat.[46]

The discrepancy may be rooted in the method of calculation, because nominal Air Force attrition rates calculated losses for a massive Soviet confrontation.[47] This model was extremely different from the problem presented by Iraq. Instead of fighting outnumbered and on the defensive against communist hordes, coalition forces were attacking a numerically and qualitatively inferior adversary. The report acknowledged the differences and attempted to account for them by making corrections based on historical evidence. Unfortunately, its examples merely cited different attrition rates but did not account for any of the other relevant differences like the size of the forces or their technological capabilities. Perhaps adding another field of study could have increased their awareness of these issues and improved their estimate.

In *The Art of Wargaming*, Peter Perla suggests that adding exercise analysis could help. He recommends a "continuous cycle of research, war games, exercises, and analysis" as a method of augmenting our understanding of reality.[48] The US Air Force exercise that serves as the foundation for this work, Red Flag, provides just such an opportunity. Unfortunately, no

attempt to extract Red Flag's lessons beyond the tactical level was available. While it is improbable that this data would have changed the outcome of Desert Storm, equipping the planners with the larger lessons may have improved their prescience about the likely results. Chapter 2 explains the applicability of Red Flag to operational planning and then attempts to extract meaning from the collected data for future reference.

Notes

1. Clausewitz, *On War*, 149.
2. Army Field Manual (FM) 6-0, *Command and Control of Army Forces*, B4–B7.
3. FM 3-0, *Operations*, 6-5.
4. Sherman, *Air Warfare*, 35.
5. Reinburg, *Air-to-Air Combat in World War II*, 10.
6. "The Defeat of the German Air Force," 26.
7. Reinburg, *Air-to-Air Combat in World War II*, 11.
8. Ibid., 15.
9. Murray, *Strategy for Defeat*, 254.
10. "The Defeat of the German Air Force," 16.
11. Ibid., 21–23.
12. Jacobs, "Operation Overlord," 277–78.
13. Luttwak, *Strategy*, 240–41.
14. Air Force Doctrine Document (AFDD) 1, *Air Force Basic Doctrine*, 22.
15. *Maintenance Metrics US Air Force*, 34.
16. Ibid., 33.
17. Grabmann, "USAF Historical Studies," 79.
18. "The Defeat of the German Air Force," 27.
19. Murray, *Strategy for Defeat*, 302.
20. Ibid., 302–3.
21. Sherry, *Rise of American Air Power*, 79, 91.
22. Lilley et al., *Problems of Accelerating Aircraft Production during World War II*, 92.
23. This statement does not suggest that America needs 50,000 combat aircraft in its inventory. Rather the intent is to highlight that changing the American aircraft industry to wartime production rates requires significant warning and years to bring it to fruition.
24. Lanchester, *Aircraft in Warfare*, 148–50.
25. Keppel and Zedeck, *Data Analysis for Research Designs*, 202.
26. Lanchester, *Aircraft in Warfare*, 55. The author used several terms to describe M over the course of his derivation. *Fighting value* is the most common, but *efficiency* and *effectiveness* are also used.
27. Epstein, *Calculus of Conventional War*, 3.
28. Fuller, *Foundations of the Science of War*, 266–71.

29. Taylor and Neta, "Explicit Analytical Expression for a Lanchester Attrition-Rate," 3–4; Epstein, *Calculus of Conventional War*, 4–7.
30. Watman, "War Gaming and Its Role in Examining the Future," 57.
31. Ibid.
32. Dupuy, *Numbers, Predictions, and War*, 33, 51.
33. Ibid., 148–50.
34. Epstein, *Calculus of Conventional War*, 4–13.
35. Biddle, "European Conventional Balance," 108.
36. Thierauf and Klekamp, *Decision Making through Operations Research*, 454–55.
37. Ibid.
38. Ball, *Fundamentals of Aircraft Combat Survivability Analysis and Design*, 143.
39. Ibid., 150.
40. E. L. Perry (Air Force War Gaming Institute/Northrop Grumman Contractor), interview by the author, 12 December 2007.
41. "Predicted Attrition for Instant Thunder Air Campaign," 1.
42. "Desert Shield Tactical Air Force Combat Losses, Damage, and Munitions Consumption."
43. United States General Accounting Office, *Operation Desert Storm*, 92.
44. Keaney and Cohen, *Gulf War Air Power Survey*, 44.
45. Ibid., 27–28.
46. "Desert Shield Tactical Air Force Combat Losses, Damage, and Munitions Consumption."
47. Ibid.
48. Perla, *Art of Wargaming*, 287.

Chapter 2

Methodology

Red Flag

Quantities derive from measurements, figures from quantities, comparisons from figures, and victory from comparisons.

—Sun Tzu
The Art of War

For more than 30 years, Red Flag has existed as the premier aerial combat training environment in the world. During that time, it has evolved significantly to prepare America's Airmen for war. By providing pilots with their first 10 combat missions insulated from the imminent threat of death, aircrews can learn to survive in a chaotic and lethal environment. Red Flag obviously retains a tactical focus to enhance the skills of aircrews from the newest wingman to the most experienced mission commander.[1] Additionally, by assembling complete aerial force packages in a single location, units have the invaluable opportunity to "train the way we intend to fight" by fully integrating the numerous aircraft capabilities of the US Air Force, joint, and coalition aircraft into a single harmonious and lethal unit.[2] By constraining the lessons of Red Flag to the tactical level, however, the US Air Force is missing an opportunity to gain operational and strategic insight into the chaotic world of aerial combat.

The combination of excellent airspace, robust threat replication, high-fidelity instrumentation, and zealous debriefs produces an unsurpassed training environment that approaches combat without actually firing live missiles, destroying equipment, and killing. The Nevada Test and Training Range (NTTR) at Nellis Air Force Base outside Las Vegas, Nevada, is an enormous combination of airspace and land ranges that facilitates large-scale aerial training. Covering approximately 12,000 square nautical miles, it provides areas for aircraft to marshal, air refuel, and fight in size similar to the geographic lanes used in combat operations.[3] In comparison to familiar recent combat

geography, figure 1 shows the NTTR over a map of Iraq. By land area, the NTTR is one-tenth the size of Iraq and twice the size of Israel. Unfortunately, the entire area is not available for use by Red Flag.

Figure 1. Nevada test and training range (NTTR) size comparison. (Reprinted with permission from *National Geographic* Society online maps).

Five primary areas divide the facility as depicted by figure 2. For Red Flag, the areas in orange, red, and blue are of major interest. Orange represents the area contested only by enemy air assets and small tactical-level SAMs. Red contains heavily defended terrain with the full array of enemy air and ground threats, houses simulated Red Air tactical regeneration airfields, and coincides with the target sets that striker assets plan to attack. As a result, the red area in figure 2 shows the scene of continuous chaos during a mission and is the location of most aircraft losses from a dense collection of SAMs and enemy aircraft. The area depicted in blue provides a location for such command and control assets as Airborne Warning and Control System and aerial refueling during the missions and is considered a blue safe area. Black is either a no-fly area, or it represents restricted areas for Red Air participants only and constitutes an area outside of the exercise. The green area usu-

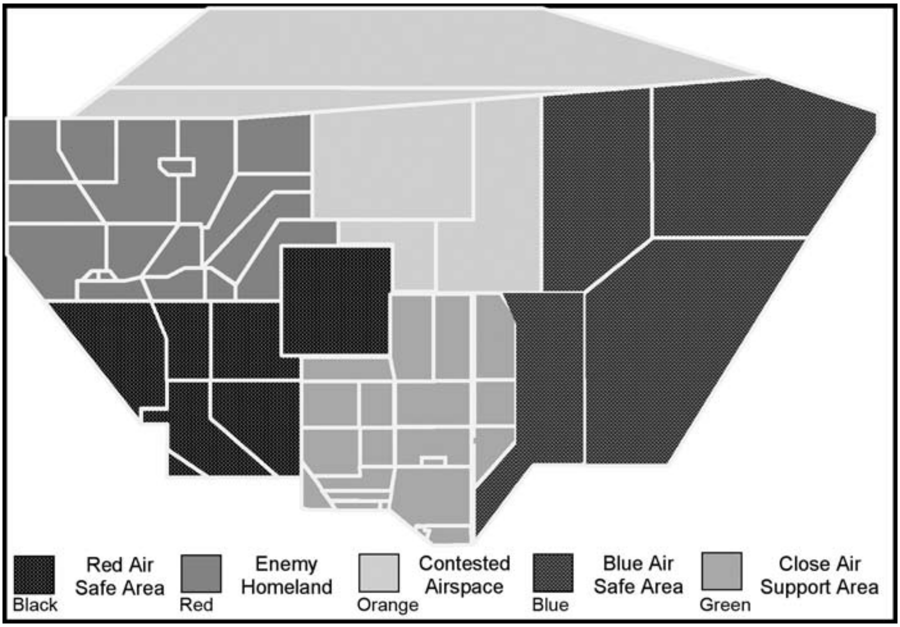


Figure 2. NTTR airspace functionality. (Reprinted from Red Flag home page [https://www.mil.nellis.af.mil/units/redflag/do/do.asp]).

ally holds close air support training and is off limits to the main strike package. As a result, the red and orange areas constitute the actual area for Red Flag combat maneuver training and cover an area slightly larger than the country of Israel. While a source of consternation for mission planners, the restricted areas are essential for training administration. They also coincidentally introduce restraints common in war. National boundaries and different mission packages in adjacent sectors can all restrict the attack breadth and direction to suboptimal levels.

The 57th Adversary Tactics Group (ATG) is responsible for adding a robust and realistic threat to the outstanding training airspace. As the premier training aid for US personnel, the 57th ATG continually refines its tactics to present an accurate representation of the full spectrum of enemy capabilities.[4] The 64th and 65th Aggressor Squadrons (AGRS) and the 507th Air Defense Aggressor Squadron (ADAS) are central to the accuracy of the simulation. Flying F-16 and F-15 aircraft, the 64th and 65th AGRS replicate the tactics, techniques, and proce-

dures (TTP) of existing and postulated adversaries. Their pilots are highly experienced and complete a rigorous training program to ensure accurate aircraft and weapons replication.[5] The 507th ADAS adds the second element of air defense by replicating adversary SAM systems within the NTTR. Using a combination of military personnel and civilian contractors, the 507th is continually refining its ability to provide the "best SAM simulation possible."[6] Unfortunately, due to the classification of this paper, the credibility of the 57th ATG cannot be discussed in detail. Based on the author's experience and interviews with operators in all three squadrons, one thing became clear: while there is always room for improvement, the threat replication provided by the 57th ATG is at least as capable as any anticipated enemy without exceeding plausible adversary capabilities.

Another great advantage the NTTR and Red Flag have over combat operations is their instrumentation through a system called the Nellis Air Combat Training System (NACTS). This system provides continuous, real-time updates on the exact locations of every aircraft on the NTTR. While this system is intentionally not used for mission execution, it provides an unparalleled capability for reconstructing the mission afterward. NACTS provides exact parameters and relationships to other aircraft that are continually available for analysis and play an essential role in ensuring the results are as realistic as possible. What used to take hours to reconstruct can be replayed in rapid succession or slowed down to a crawl for detailed scrutiny. As a result, outcomes become less ambiguous and more accurate. This accuracy leads directly to the ability to find root causes for errors, learn from those mistakes, and improve performance the next day. This truth data also prevents the traditionally heated debriefs from degenerating into debates about sequences and outcomes. In total, the synergy of excellent training airspace, adversary support, and accurate post-mission analysis adds greatly to the training environment.[7]

Limitations

Despite these geographically and technologically enabled benefits, some shortcomings in the Red Flag scenario and their execution ensure results will never exactly mirror combat con-

ditions. First, real-world intelligence is never perfect. America's next test in combat may face tactics or weapons previously unknown or unimagined. Such surprises inevitably occur in war. If there is a flaw in the current threat replication, that flaw relies on the precision of intelligence. Adversary crews strive for precise replication of tactics but are rarely free to improvise. As a result, a critical piece of the war is missing from the exercise. War is a conversation between opposing sides.[8] In its current state, Red Flag is muting half of the dialogue by constraining its aggressor operators from using their systems to the best of their ability. On one hand, this policy makes sense because it provides Blue Air a consistent set of assumptions to fight. Unfortunately, it also trains crews to trust intelligence data implicitly and to solve the problem of aerial combat mechanically. This could lead to a catastrophic problem where units cannot improvise in the face of new enemy tactics not predicted by intelligence sources.

Second, despite the chaotic, free-flowing environment presented by Red Flag, the emotional stress falls well short of combat. Undoubtedly, the capabilities of new wingmen to perceive, comprehend, and react to complex scenarios are greatly enhanced over the course of a two-week Red Flag. The true effects of combat are knowingly absent because real missiles are not flying and losses to enemy action only draw repercussions during debrief. Imagine the difference in a flight leader's mentality launching on his third Red Flag sortie determined not to get another wingman "killed." Then compare that to the emotions of the same pilot launching on a combat sortie back to the same area where his wingman ejected the day prior. Some will react in a highly competitive way determined to make a mark on the enemy, while others may face severe anxiety leading up to the sortie. While the courage to "press on" despite the loss of a wingman is required in both events, Red Flag obviously falls significantly short of combat emotions.[9] Only placing an individual in the real scenario will reveal a true reaction.

Third, since Red Flag is a training exercise, safety takes precedence over realism. In most cases, sound tactics equate to safe execution, and there is no effect on the flow of the mission. Sometimes, however, deconfliction takes the front seat. In these instances, pilots elect not to make a full defensive ef-

fort against the exercise threat and instead ensure deconfliction from other flights in the area. The result is often an official "kill" due to lack of maneuvers when in reality the crew may have survived the same scenario during combat. Similarly, night missions often require aircraft to maintain specific altitudes for the entire duration to guarantee deconfliction from stealth aircraft. This measure for training safety restricts tactical effectiveness and would likely lead to decreases in attrition rates for both sides. The desire for deconfliction does not fade during combat operations. Similar schemes are apparent in combat missions, but pilots are more likely to deviate from planned parameters when the need for survival outweighs the perceived risks of safety.

Fourth, the shot-kill criteria used to determine the outcomes contain known errors that preclude their use as true results. The 83d Fighter Weapons Squadron uses extensive testing through live missile launches with operational squadrons to verify air-to-air weapons capability. The results of the testing go directly toward building detailed models of missile capability throughout their flight to a target. Despite this accuracy, pilots must analyze their shots in real-time while tactically executing a stressful mission. As a result, simplified rules of thumb substitute for complex computer models and enable a sufficiently accurate kill-removal process to take place within the framework of the exercise. This simplification leads to conservative results and potentially fewer than expected kills.[10] On the other end of the spectrum, probability in the exercise becomes a binary, yes-or-no solution. Missiles do not work this way. Each missile will have a varying chance of killing its target between 0 and 100 percent. Actual missile probability of kill (P_k) is determined by the equation: $P_k = P_h P_{k/h}$.[11] Probability of hit (P_h) represents the probability of a missile hitting its target. This factor accounts for a complex sequence of events including the missile launch sequence, guidance phase, and fusing at the target. For the training scenario, P_h varies based on simplified understanding of the missile's capability and is 0, 50, or 100 percent effective depending on several factors. Oversimplification leads toward an optimistic result, since most valid shots result in a 100-percent training P_h. The probability that a hit will result in a kill ($P_{k/h}$) is a gauge of target aircraft survivability

measured against the missile. Real-world $P_{k/h}$ varies by aircraft based on the specific element of its design in relation to the weapon.[12] In the training simulation, $P_{k/h}$ equals 100 percent for all fighter aircraft. Modern aircraft designs specifically attempt to reduce their vulnerability to missile impact. With numerous examples of aircraft returning with significant combat damage, it is obvious that $P_{k/h}$ is less than 100 percent. An irreparable aircraft sitting on a friendly airbase, however, is just as useless as a crashed one except that a search and recovery mission would not be launched for the downed aircrew. Even reparable aircraft will remain out of the usable inventory for a fixed time before returning to duty. The result is optimistic by forecasting target destruction with every impact. Fortunately, the conservative simulation model and the optimistic missile P_k tend to offset each other. The result is a usable approximation of missile capability, but it will skew the accuracy of the findings away from actual results.[13]

Despite the previously discussed limitations, the Red Flag exercise results in a near-combat experience usable to model modern aerial combat. Since the same conditions influence both sides, the relationships between the opposing forces should remain near their natural, wartime character. The final attrition numbers will inevitably vary from the results of a combat engagement, but they should mirror combat relationships. As a result, it is important to emphasize that the useful part of this analysis will lie in the linkages and not in the specific values of the data. While using this analysis may prove fruitful for anticipating the results of future Red Flag missions, attempting to use the specific results of this data for real-world planning would likely lead to erroneous conclusions and poor strategic decisions. Therefore, Red Flag can serve as a reasonable model for modern combat and is useful for representing combat experiences within the scope of this thesis. The patterns and relationships are therefore the focus of analysis.

Assumptions

In addition to the previously discussed tactical limitations within the Red Flag scenario, some operational level assumptions are required to frame the applicability of the data. Pri-

mary among them is that Red Flag replicates a near-peer competitor with comparable resources to the deployed US military force. The adversary is capable of investing in not only a robust military architecture but also a military force of highly trained professionals who are ready to fight.

Next, the Red Flag scenario does not account for the effects of bombing on future sortie generation for either side. This is most similar to Colonel Warden's Case IV—limited options. In this case, airfields and rear areas are immune from attack either because of "political restraints or because of the physical inability to reach appropriate targets."[14] One example of this scenario is the fight for aerial supremacy during the Korean War when both sides left plans for attacking enemy airfields off the table due to fears of escalating the war toward open global conflict.[15] These political limitations are an unfortunate but occasionally necessary element in warfare that affects the range of options available to military commanders. The Red Flag data may also have utility in other scenarios, but the correlation will be less direct.

Finally, the Red Flag tactics on both sides are high risk, and leaders expect losses. Red Air methodology focuses on a mentality of defending its homeland but also accounts for Blue Air training requirements.[16] Similarly, Blue forces execute using a high-risk mentality where losses are acceptable for mission accomplishment. The result is a fight for survival mentality that guarantees attrition on both sides. This mentality is also common throughout history, with the strategic bombing campaign against Germany during World War II serving as an example of how high-risk missions can produce elevated attrition rates. Changes in acceptable levels of risk for either side would likely decrease the frequency of aerial confrontation but should not affect the attrition values for individual battles within the larger campaign.

Data Set

This study uses Red Flag as a quantitative model to highlight and explain the relationship between mass and technology in aerial combat to advance operational and strategic thought regarding the relationship. This daunting task, if taken as a

whole, could lead to an unusable situation confused by the limits of training and result in sweeping generalities irrelevant to strategic and operational users. Instead, by focusing on a single mission area with the fewest possible variables, trends become clearer and correlation more direct.

Red Flag's focus on offensive operations necessitates further focus on the role of OCA in creating air superiority. AFDD 2-1.1, *Counterair Operations*, defines OCA as "offensive operations aimed at destroying, disrupting, or degrading enemy air and missile threats."[17] OCA defines a spectrum of actions that range from direct kinetic attacks by dropping bombs on enemy airfields, known as OCA-surface attack, to the less invasive electronic jamming of enemy surface-to-air radars that is part of OCA suppression of enemy air defenses (SEAD). Within that continuum of aerial combat, one mission, OCA sweep, seeks to destroy airborne enemy assets before they engage other friendly aircraft. The sweep mission holds a unique place with the Red Flag exercise. In the interest of training, friendly strikers, SEAD players, and other friendly aircraft in the exercise continue on their mission after an enemy attack to facilitate their training. Sweep players, on the other hand, exist within the scenario and face immediate kill removal during execution. Kill removal is not permanent, since sweep players can regenerate after exiting the fight area, but the immediate removal ensures that the sweep scenario more closely replicates the lessons of combat.

Focusing on the initial OCA-sweep missions inside the exercise provides several other advantages. First, the F-15C, the primary OCA-sweep aircraft of the US Air Force, has changed little between 2001 and 2005. Despite updated software suites enabling subtle new capabilities, its primary tactics and weapons have remained similar for the entire period. Critical capabilities like beyond visual range (BVR) identification, Link-16 data sharing, and the advanced medium-range air-to-air missile (AMRAAM) have remained constant throughout the period. Significant additional capabilities include the joint helmet mounted cueing system and the AIM-9X heat-seeking missile in 2004–7. While these systems greatly enhance the F-15C's lethality in a visual engagement, most of the engagements occur with the AMRAAM at longer ranges. Therefore, a significant difference between the results should not exist. By further fo-

cusing the investigation on ingress results, the data remains less affected by the friction of the training environment. After the initial sweep, "killed" aircraft clutter the airspace transiting toward regeneration areas or returning to base. This added ambiguity often leads directly to artificial results from erroneous tactical decisions based on poor situational awareness and the inability to identify enemies as dead or alive. The ingress sweep phase, however, does retain the positive stresses of Red Flag, since both air and ground threats are present.

Arcata Associates, Inc., under contract to the US Air Force since 1999, collects the data used in this thesis for assessing the effectiveness of units during the course of each two-week Red Flag exercise. Each data point was collected during the detailed debriefs after each of 784 missions.[18] Although Arcata employees are not involved in the analysis process, they personally record the arbitrated debrief results and consolidate the information into a single source database for each Red Flag. A macro consolidates individual Red Flag databases into a single document for analysis. Extracting additional information on threats from the Air Combat Command after action reports provided the data necessary to analyze the effects of adversary tactics on mission results. Unfortunately, since the reports were generated to summarize training and not facilitate analysis, several are missing data or lack the detail necessary to be useful in this study. As a result, the viable data set decreased by 338 missions (216 before 2001; 42 in 2001; one in 2002; 60 in 2005; and 19 in 2006) to 446. Additionally, a major change in the Red Flag scenario occurred starting in 2006. Red Flag added several new scenarios, and the adversary threats shifted significantly to replicate a modernized threat scenario. While this is a great enhancement for US Air Force training and readiness, it represents a qualitative shift in the data for this analysis. While data collected starting in 2006 should more accurately represent a fully modernized adversary, the small number of available data points and additional scenarios hinders this analysis.[19] As a result, the remaining 320 missions from 2001 to 2005 provide a focused data set with reasonably consistent conditions for analysis.

Within the 320 remaining missions, no OCA-sweep aircraft launched on six missions, and a single F-15C that launched

without additional OCA support accounted for another: all seven cases were removed. Additionally, four missions dropped out because they recorded zero losses on both sides for the ingress sweep. This was likely due to an in-flight emergency or other training-related termination of the fight. Arcata deletes incomplete results caused by administrative procedures.[20] Finally, Red Air presented a MiG-21 threat on two missions in 2004. With only two missions, they represent no statistical benefit for the analysis and were deleted. This left 307 effective missions with 299 containing F-15Cs as the primary or sole element in the sweep. The *N* of 299 missions is the basis for the analysis, except when analysis requires the additional information.

The data set covers the results of execution for each flight of aircraft regardless of mission and includes basic measures of effectiveness depending on the specific mission area. As a result, air-to-air engagements and air-to-ground mission success rates are available for each flight. One difference between air-to-air and air-to-ground data collection is the break point between the ingress and egress units of measure. The dividing line for air-to-ground missions is weapons release on target. Air-to-air ingress data transitions at the reset of the preliminary aggressor tactic.[21] This difference in break point leads to an inaccurate accounting of aerial kills between strikers and aggressors since striker ingress can take place after the first presentation. As a result, it is not possible to correlate striker losses or air-to-air kills using this data.

Data Analysis

The analysis used both Excel and Statistical Program for the Social Sciences (more commonly referred to as SPSS) version 12.0.1 to determine the significance of results and produce the outputs for this paper. Statistical tests used in this analysis to determine significance and correlation include frequencies, percentages, correlations, t-tests, and analysis of variance (ANOVA). Correlations will use Pearson's correlation coefficient. Tukey's honestly significant difference (HSD) post-hoc analysis methodology will support initial ANOVA results, assuming Levene's test for homogeneity proves insignificant. Regression analysis using the method of least squares provided the predic-

tive trends of future results. Analysis relied on the 0.05 level of significance for evaluation.

Since Red Flag is a training environment, it is essential to understand when changes in attrition are due to changes in participant training level. Traditional lore would predict a decrease in Blue and an increase in Red attrition over the two-week exercise due to increased aircrew proficiency. The threat, however, continually increases over the same time-span. Logic would therefore suggest an increase in Blue and a decrease in Red attrition over the same time span. Figure 3 shows the averages for both F-15 and Red Air ingress attrition broken out by week and day.

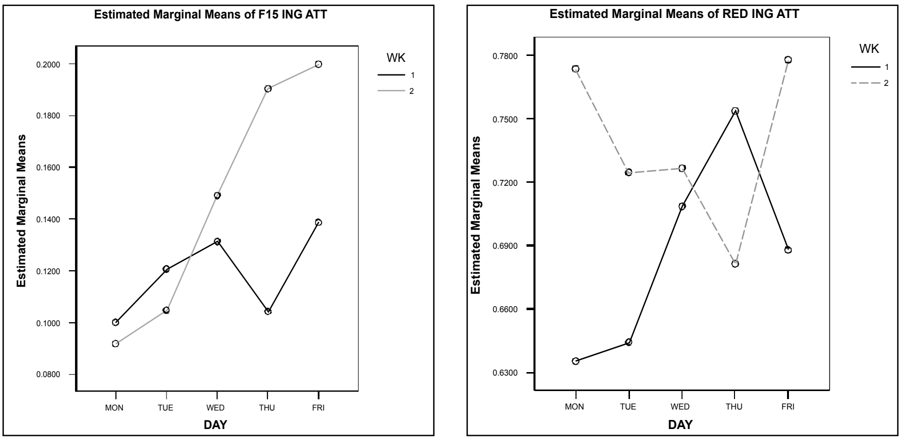


Figure 3. Daily attrition variation.

Contrary to the expected decrease in F-15C attrition, figure 3 indicates a trend of increasing attrition over the course of both weeks one and two. Additionally, attrition is nearly identical or greater in week two when compared to the same day in week one. This is exactly opposite of the expected results if training and pilot skill were the only factors. A T-test indicates no significant differences in the attrition between weeks one and two. ANOVA analysis also indicates no significant variation amongst the days for each week except for between Monday and Thursday on week two (p=0.045). The Red Air trends match more closely the expected results. Week one follows a gradual in-

crease in Red losses, while week two remains relatively constant, but neither analysis indicated any statistically significant variation in the averages. As a result, the trends indicate that the increase in the scenario's difficulty likely exceeds the increased skill over the course of the week (appendix A3).

Between 2001 and 2005, F-15C attrition decreased, and Red Air attrition increased over the same period as indicated in figure 4. ANOVA analysis indicated a significant variation in both F-15C (F=2.993/p=0.019) and Red Air (F=12.627/p= 0.000) attrition (appendix A1). Tukey's HSD test revealed a significant difference in F-15C attrition between 2001 and 2004 (p=0.012) only. Similarly Red Air attrition in 2001 varied significantly (p=0.000) between all other years.

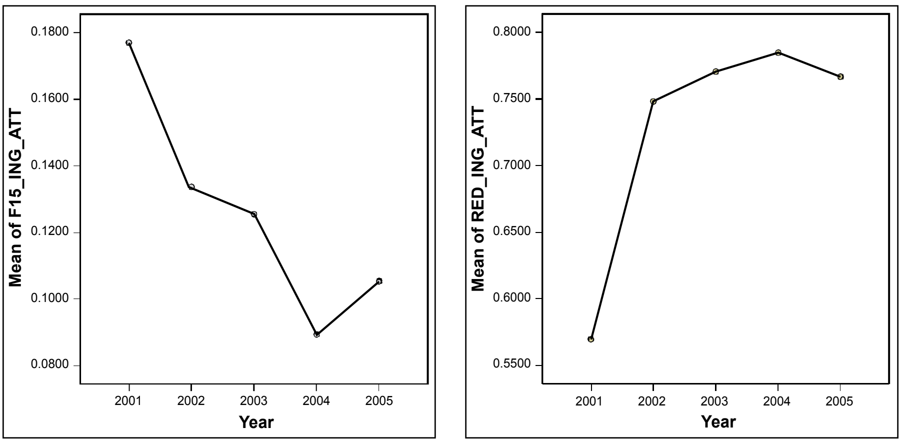


Figure 4. Yearly attrition variation.

Further inspection of 2001 reveals insignificant variation in F-15C attrition but significant variation in Red Air attrition (F=3.015/p=0.024 in appendix A2). Tukey's HSD test indicates Red Flag 2001 3-2 varied significantly from 2001 4-2 (p=0.019) as depicted in figure 5. The Red Flag 2001 3-2 after action report indicated weather problems that forced mission changes and restrictions to account for exercise safety. Interestingly, the initial suggestion is that adverse weather decreases Red Air attrition. Normal safety precautions cuff Red Air maneuvers during weather days and would therefore suggest an increase in Red

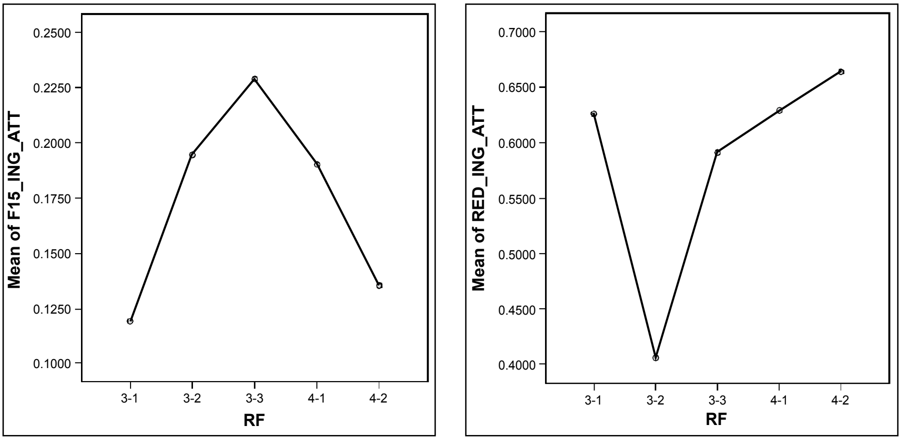


Figure 5. 2001 attrition variation.

Air attrition due to more predictable and therefore less-effective maneuvers. Unfortunately, Arcata data does not track weather conditions or restrictions sufficiently to explore the ramifications of weather on attrition occurring on all Red Flag missions.

The counterintuitive trend, however, suggested there might be another source for the changes in attrition. Checking for variation in other factors reveals that the 2001 anomaly is more likely due to differences in simulation instead of weather. Using an ANOVA test to analyze the numbers of aircraft flown on each side in Red Flag 2001 3-2 indicates a significant change in the numbers of aircraft flown. F-15C numbers increased slightly from a year average by approximately one sortie per mission to 8.53 ($p=.024$), while Red Air sorties increased by over three sorties per mission to 11.67 ($p=0.000$).

Taking this observation and stepping back to the yearly analysis reveals a similar trend. The year 2001 boasts the highest number of Red Air sorties and a comparatively low number of F-15C sorties when compared to 2002–2005. The significantly higher than average F-15 attrition and lower Red Air attrition in figure 4 noticeably corresponds with the significantly higher than average ($p=0.001$) number of Red Air in 2001 as depicted in figure 6. Similarly, the Tukey HSD test confirms a significantly lower number of F-15C sorties in 2001 as compared to both 2002 and 2004.

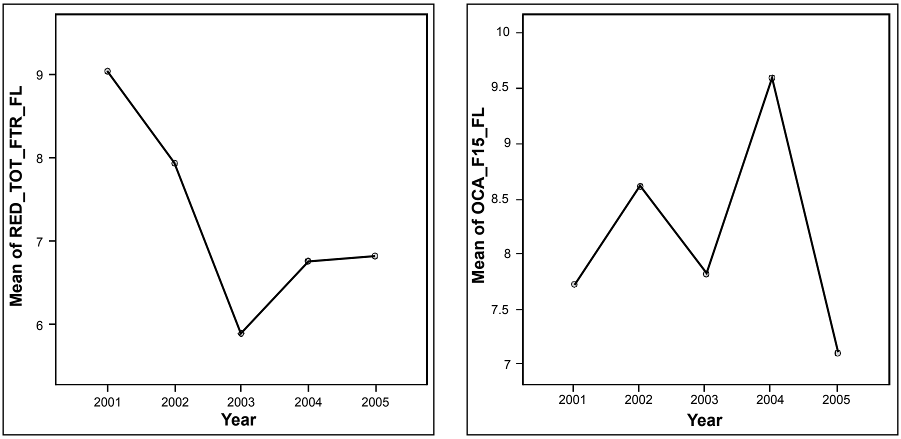


Figure 6. Yearly average sortie variation.

The trend becomes clearer by transforming the raw numbers of aircraft into a force ratio. Dividing the total number of F-15C aircraft on a mission by the total number of Red Air present provides a simple number comparing the relative strength of each side. Force ratios greater than one indicate F-15C numerical advantage, while quantities less than one give the advantage to the Red Air. Figure 7 clearly depicts the difference in force ratios between 2001 and 2002–2005, because it is the only year when on average Red Air outnumbers F-15C aircraft (appendix A1). ANOVA testing confirms the difference (F=18.539/p=.000). A follow-on Tukey HSD test confirms that 2001 is significantly different from 2002 (p=0.008), 2003 (p=0.000), and 2004 (p=0.000).

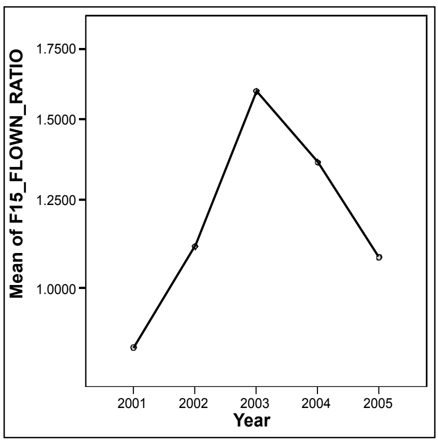


Figure 7. Yearly force ratios.

By comparing figure 7 to figure 4, the correlation between force ratio and attrition becomes clearer. The year 2001 is characterized by the only force ratio numerically

in favor of Red Air. Predictably, F-15C attrition is highest, and Red Air attrition is lowest in 2001. A Pearson two-tailed correlation test confirms the association (appendix A10). Using the logarithm of the force ratio, F-15C attrition correlates at -0.297 (p=0.000), and Red Air attrition correlates at 0.396 (p=0.000). Neither correlation is strong enough, from a purely scientific standpoint, to suggest this is the sole cause. However, given the chaotic nature of combat and the other independent variables present, this is expected. Additionally, the high level of significance suggests utility in using force ratio for predicting attrition on both sides over using only the historical average.

This common measure of relative strength, however, is not without shortcomings. First, it tends to mask the increasing complexity of large formation battles. For example, a one-versus-one duel is numerically equal to an exceedingly chaotic 100-versus-100 mêlée. Since the Red Flag scenario is built around eight scheduled F-15C sorties, this issue becomes less of a problem, but it has the potential to give false impressions if the data is extrapolated to very large or very small formations. Additionally, the ratio compresses Red Air numerical advantages into a small range between zero and one, while F-15C advantages range from one to infinity. Representing all ratios on a logarithmic scale easily alleviates this problem by balancing the presentation around the 1:1 ratio.

The suggestion that an increase in the number of opposition forces will negatively influence the outcome of the engagement is as old as war itself and is useless without understanding how other variables interact with it. In addition to the number of aircraft on each mission, Arcata collects data on 12 other independent variables. As explained earlier, weather data is not collected, but sorties are broken down between day-and-night missions. Recent combat experience suggests American night vision goggle (NVG) tactics should represent a distinct advantage. Initial analysis of the entire data set using an independent samples T-test indicates F-15C attrition drops by 3.67 percent (p=0.037), and Red Air attrition increases by 6.43 percent (p=0.014) during hours of darkness (appendix A4). This potential difference is explored with better fidelity later in this analysis by including such additional variables as adversary weapons and tactics within the final data set. For now, with a

10 percent difference in attrition favoring Blue Air, the night advantage needs further exploration.

The remaining 11 variables describe the capabilities of the adversary and include threat aircraft, weapon, threat tactics, electronic attack, regeneration rate, reaction level, maximum number of live groups, surface-to-air missile rules of engagement, surface-to-air missile proficiency, communications jamming, and ground-based radar jamming. Attempting to analyze each variable independently led to insignificantly small groups that yielded little or no useful information. Factor analysis (appendix A11) suggests two discrete groups for examination in addition to the force ratio and day/night variables already discussed.

The first and largest group includes nine tactical variables used to describe the adversary's less-obvious technical and training capabilities. The first five—tactics, electronic attack, regeneration rate, reaction level, and maximum number of groups—all directly influence the OCA-sweep mission. Two variables, SAM readiness levels and SAM rules of engagement, deal directly with the ground threat. Although apparently extraneous to this analysis, these variables may affect the ability of OCA-sweep aircraft to pursue Red Air into hostile territory and add to the chaos of the operational environment. Finally, Radio Electronic Combat and Big Crow simulate ground-based jammers and their effects on Blue performance. Unfortunately, the Red Flag training environment adjusts the whole group of variables simultaneously to replicate an overall threat change. As a result, a Pearson Bivariate Correlation test reveals that the variables significantly correlate to each other ($r \geq 0.501$, $p=0.000$) except maximum number of live groups ($r \geq 0.302$, $p=0.000$) (appendix A9). This indicates the variables change—together within the scenario and, therefore, the effects of individual variables—are unfortunately beyond the fidelity of this data.

The second group, consisting of adversary aircraft and weapons capabilities, is more useful. Threat aircraft simulations include MiG-23, MiG-29, and SU-27 by the 57th ATG aggressor aircraft. Between 2001 and 2005, F-16s replicated this significant spectrum of threat capabilities. Although aggressor threat-replication standards try to replicate enemy capability accurately, there is the potential for an undesired uniformity in

performance. This is especially apparent at the merge, where actual aircraft flight characteristics are most prominent. In the radar missile BVR engagement, however, aggressor replication specifically restricts the use of aircraft systems and reactions to match expected threat capabilities.[22] A threat aircraft ANOVA analysis suggests a significant variation in attrition for F-15C ($F=6.562/p=0.002$), but Red Air variation is insignificant. With sufficient homogeneity, the Tukey HSD comparison shows significant variation between both the MiG-23 and MiG-29 when compared with the SU-27 simulation for the F-15C ($p=0.005/p=0.020$) attrition. Variations in Red Air attrition were insignificant (fig. 8 and appendix A5).

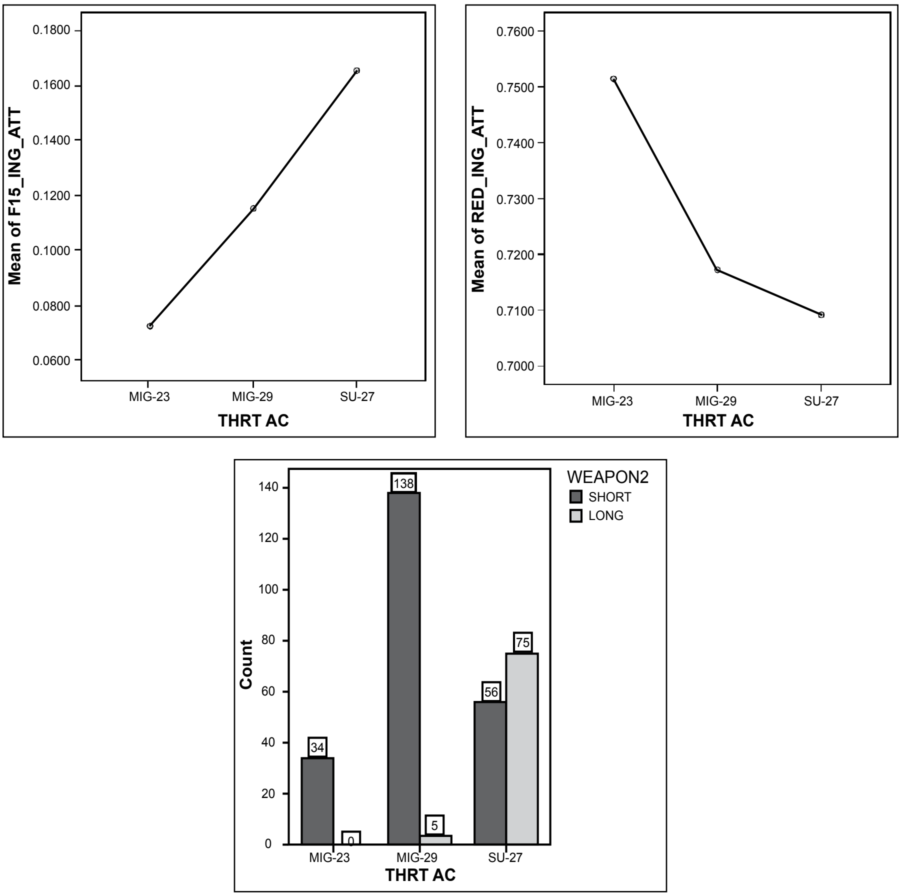


Figure 8. Attrition variation versus threat aircraft.

Similarly, threat weapons capability follows an almost identical path (fig. 9). Aggressor threat matrices weapons categories included short (MiG-23/N=34, MiG-29/N=138, SU-27/N=56) and long (MiG-29/N=4 and SU-27/N=75) air-to-air missile simulations. T-test analysis identified significant variation within both F-15C (p=0.012) attrition with Red Air attrition being insignificant (appendix A6). This mixed combination of weapons and simulated aircraft makes determining differences between the MiG-29 and SU-27 simulation difficult. Holding one variable steady and then analyzing the other simplify this problem.

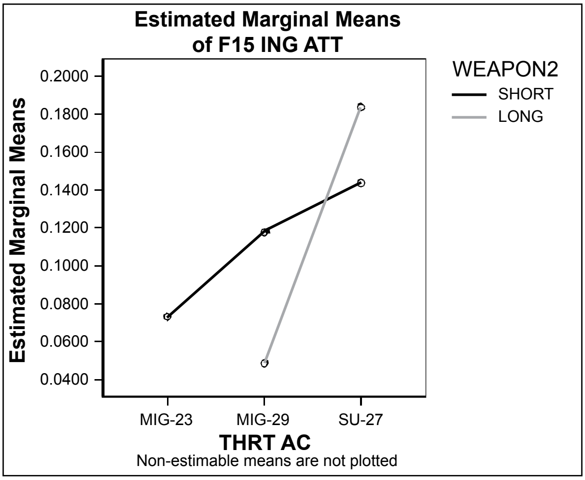


Figure 9. Threat weapon and aircraft comparison.

First, by selecting only the short weapon and second running an aircraft ANOVA analysis, no statistically significant difference appears in any of the three attrition categories, despite a mean increase in attrition proceeding from the low MiG-23, through MiG-29, to SU-27. Similarly, an independent sample T-test comparing MiG-29 and SU-27 with short weapons results in no significant difference. With the long missile MiG-29 (N=4) small sample size, no adequate comparison is feasible. Looking at the SU-27 and comparing the short and long missile also produce an insignificant difference in any of the three attrition rates. By correlating MiG-29 aircraft with short missiles and SU-27 aircraft with long missiles, a significant difference

emerges for the F-15C (p=0.025). Similarly, by adding MiG-23 short missions back into the mix with the MiG-29, the significance continues for F-15C (p=0.004) attrition (appendix A7).

This grouping of the MiG-23 and the MiG-29 with the short missile compared to the SU-27 with the long missile provides many advantages for analysis. First, both data sets provide relatively large sample sizes (N=239) as depicted in figure 10 with significant variations in Blue Air attrition between day and night (appendix A8). Additionally, the pairing presents two different categories of enemies. The short MiG-23/29 pair represents a country with an early fourth-generation fighter capability similar to the threats America faced in Operations Desert Storm and Allied Force. The long SU-27 combination represents a country further along the technological road attempting to compete qualitatively with the F-15C. This dialectic provides the metaphor for analysis in this thesis. First, the short MiG-23/29 scenario provides sufficient data for attrition trend identification and the Blue versus Red comparison. With the relevant factors and decision points identified, the long SU-27 scenario introduces a change in enemy technology, which facilitates the exploration of the ramifications on Blue capabilities.

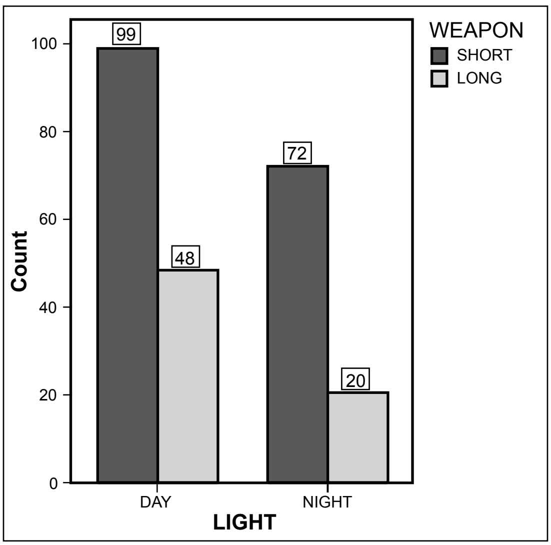


Figure 10. Final data breakdown.

With the final data set defined for study, it is time to try to find order in the chaos of combat. Since this thesis explores relationships and does not seek to gain specific values for prediction, analysis focuses on comparisons with the intent of highlighting relationships for future study. Before proceeding further, however, it is important to confirm the previous observations within the final data set. Running a Pearson two-tailed correlation test with the entire group (N=239) indicates continued significant correlation between the force ratio and F-15C (-0.304/p=0.000) and Red Air (0.368/0.000) attrition (appendix A12). Additionally, F-15C attrition correlates with the aircraft weapons pairing (0.214/p=0.001), but Red Air does not change significantly. Finally, day/night does not represent a significant correlation for either F-15C or Red Air attrition within the final data set. With that in mind, analysis focuses completely on the short MiG-23/29 and the long SU-27 relationship to infer the potential ramifications of the enemy introducing new technology on the battlefield.

The short MiG-23/29 scenario provides the starting point and therefore requires a detailed explanation of the relationships and analysis. This process attempts to extract useful information from the confusion of Red Flag. Figure 11 contains scatter plots of both F-15C and Red Air attrition plotted against the logarithm of the force ratio.

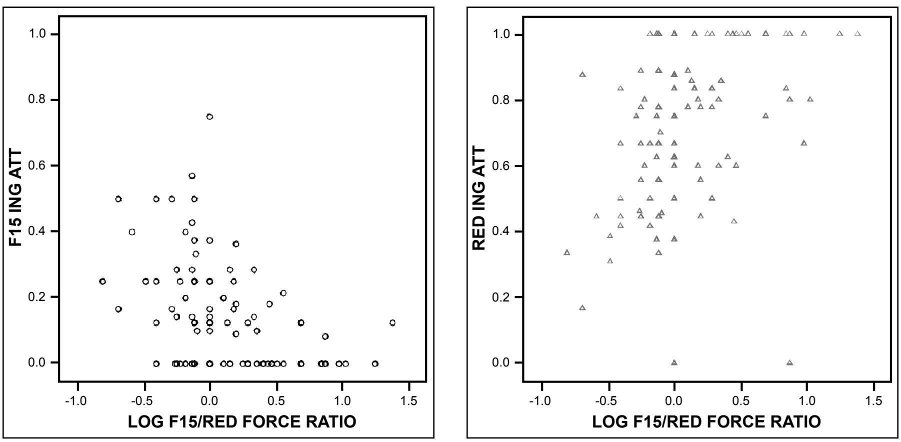


Figure 11. MiG-23/29 short scatter plot.

Although neither the F-15C nor the Red Air data groups neatly around a central line, the general trend is clear: increasing the force ratio for a mission results in decreasing F-15C and increasing Red Air attrition. Another way to visualize this trend is by using a box plot as shown in figure 12. It helps to visualize trends in the data not initially evident in the scatter plot. Each line indicates a single force ratio and the variance of the data with the solid area representing the central 50 percent and the whisker reaching out to accommodate most of the remaining data. Points with numbers next to them indicate outliers from the main body of the data. The dark mark near the center of each indicates the median value.

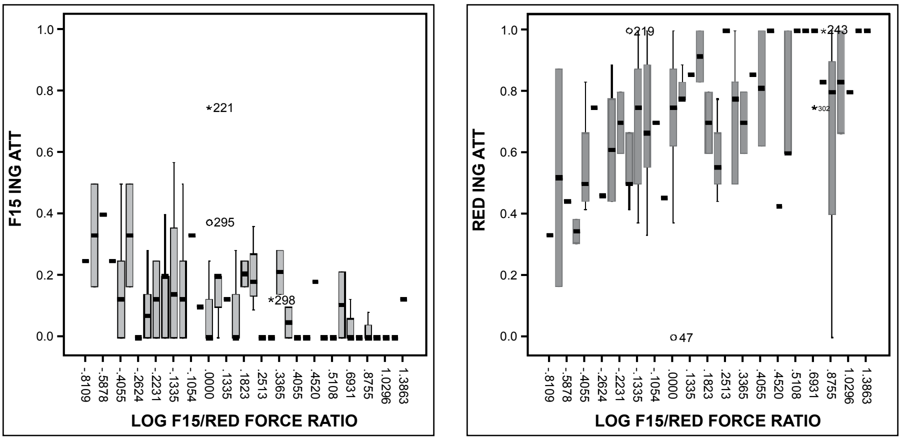


Figure 12. MiG-23/29 short attrition box plot.

This chart again supports the correlation between force ratio and attrition. Therefore, regression analysis may provide a useful equation to represent the data. While several non-linear regression methods may eventually prove more applicable to a larger data set, basic linear regression based on the logarithm of force ratio is most applicable in this case for two reasons. First, since Red Flag is a military exercise and not a scientific test, the data is not evenly distributed. Instead, figure 13 reveals a nearly normal distribution of data centering on an even 1:1 force ratio (i.e., log[1] = 0), which falls in line with normal exercise planning factors of scheduling nearly equal numbers

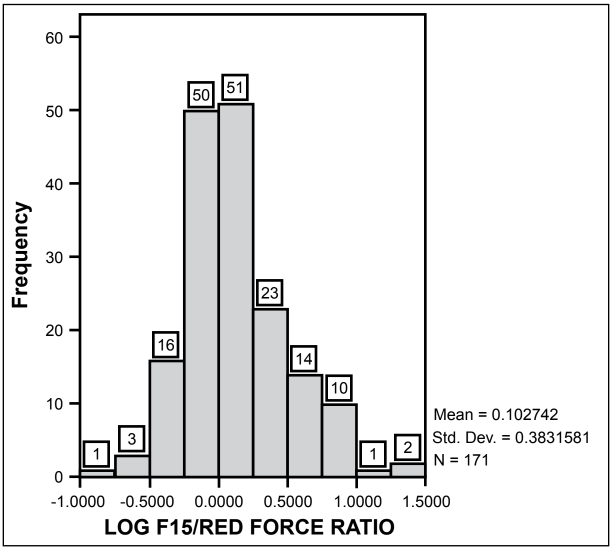


Figure 13. MiG-23/29 short force ratio histogram.

of air-to-air sorties for each side. As a result, the data confidence is best in the center and becomes less reliable at both extremes. The second problem with the data is that the data do not cover the entire range of possible outcomes. While both F-15C and Red Air attrition appear to anchor near their extremes, approaching 0 percent and 100 percent attrition respectively, on the right side of figure 12, neither side approaches the opposite extreme. This missing data leave much doubt about the natural trends as the force ratio moves left and favors Red Air. With these limitations in mind, linear regression provides a baseline analysis. Future studies with more complete data, however, may suggest other, more complex relationships.

Forward stepwise regression using the tactical variables recommends eliminating the other factors from the analysis except force ratio (appendix B1). Figure 14 represents the regression results for both F-15C and Red Air with representations for error analysis. Taking a closer look at both the F-15C and the Red Air data reveals several trends common in this analysis. First, ANOVA testing indicates that the regression line accounts for only about 14 percent of the data variation but that the variation is not due to chance for either the F-15C (F=26.078/p=0.000) or Red Air (29.618/p=0.000). Similarly, the model's

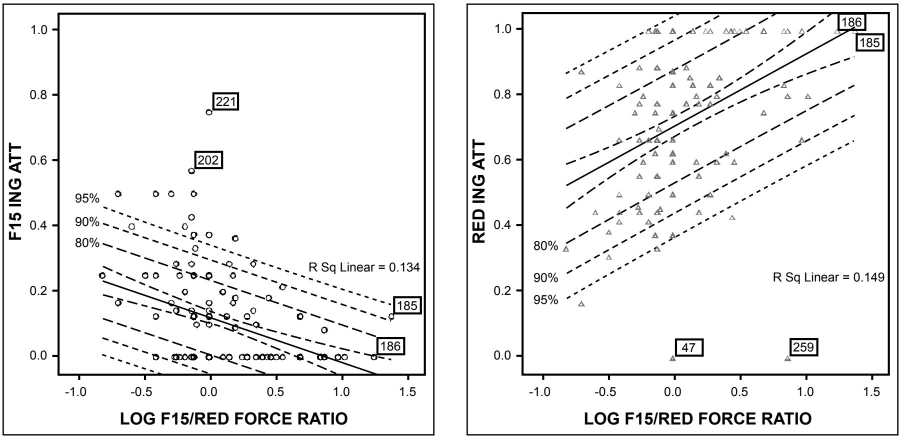


Figure 14. MiG-23/29 short regression results.

R-squared values of 0.134 for the F-15C and 0.149 for Red Air corroborate the weak correlation but also suggest that using the model is better than using the average attrition alone. Casewise diagnostics highlight two outliers for each case highlighted in figure 14 (F-15C–#s 202/221, Red Air–#s 47/259). Additionally, points 185 and 186 have disproportionate influence on the regression for both sides. In all cases, historical data did not indicate any influences that would suggest any reason to exclude the data and inclusion did not detract from correlation. Therefore, their influence is noted, but they remain as part of the analysis.

Using the same forward stepwise multiple regression technique for the long SU-27 scenario did not work as smoothly. Initial ANOVA testing suggested a weaker correlation for the F-15C (F=3.454/p=0.068) but significant correlation (F=7.310/p=0.009) for Red Air (appendix B2). Two points (119/228) had excessive influence within both data sets. Again, neither case suggested abnormal circumstances for the scenario, but 228 was a Friday night mission on the second week of a Red Flag. Normal Red Flag protocol requires units to depart on Saturday to make room for follow-on units. Therefore, pilot motivation to shorten the debriefing process by minimizing shots and kills may have decreased performance, but there is no specific evidence to support this hypothesis. While this speculation is not

sufficient in and of itself, the small data set is less tolerant of abnormality. By removing mission number 228 from the data set, the regression returns to the same pattern observed in both of the short MiG-23/29 and the Red Air long SU-27 analyses for the F-15C (F=5.778/p=0.019) and Red Air (F=7.531/p=0.008) as depicted in figure 15. With that in mind, mission 228 was removed from the analysis as an anomaly but kept in the database for future use. Other outliers were retained in the analysis. As expected with the smaller data set and large variance shown in figure 15, the error size is larger but still better than using the mean to predict attrition.

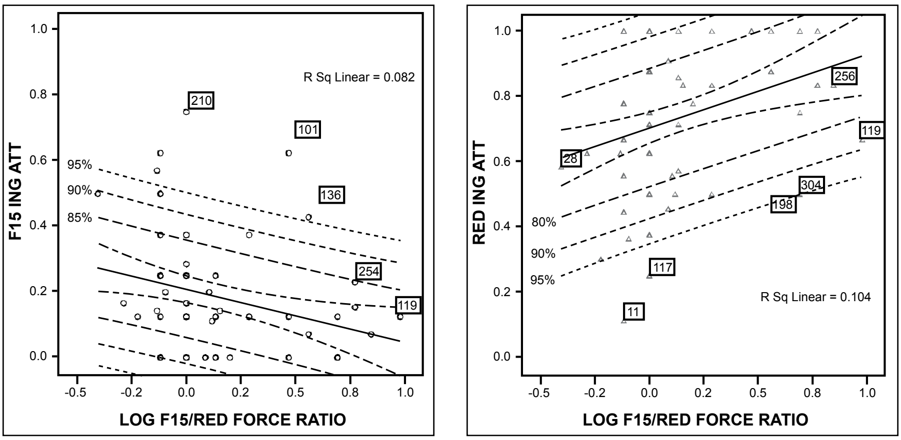


Figure 15. SU-27 long regression lines.

Before moving to the explanation of the results, it is important to explain one of the limitations of the linear regression lines. Attrition values cannot logically exceed 100 or go below 0 percent. On the low end of the spectrum, some aircraft will inevitably fail due to mechanical problems or pilot error. Similarly, no matter how disadvantageous the scenario, a chance for survival always exists. As a result, a complete data set would logically indicate a line approaching a logistic curve with both extremes asymptotically approaching but never reaching either 0 or 100 percent. To prevent the regression lines from violating the limits of reality, their values have arbitrarily been limited to between 0.5 and 99.5 percent. Future studies should adjust

these values based on observed and calculated data not available in this study.

The four regression models just discussed form the basis of analysis for the remainder of the study. Their wide confidence intervals combined with the disproportionate influence of a few outliers highlight the inadequacy of the data from a scientific standpoint. The consistency between the four models, however, suggests a baseline validity to the correlation between force ratio and attrition. Chapter 3 makes use of these models to suggest methods commanders and planners can use for future planning efforts. The inaccuracies inherent in the regression models caused by the training environment skew the values away from similar data collected for testing purposes. Therefore, the specific values calculated in the following pages attempt to explain a thought process and highlight decision points instead of making predictions about real world combat.

Notes

1. "Tenets of Red Flag."
2. Ibid.
3. Nevada Test & Training Range (NTTR) Briefing.
4. Col David R. Stilwell (Commander, 57th Adversary Tactics Group), interview by the author, 5 December 2007.
5. Lt Col Steven D. Imonti (64th Aggressor Squadron/DOO, Aggressor 1995–2007), interview by the author, 3 December 2007.
6. Lt Col Robert J. Smith (Commander, 507th Air Defense Aggressor Squadron), interview by the author, 4 December 2007.
7. Lt Col Thomas A. Bouley (Deputy Commander, 414th Combat Training Squadron–Red Flag), interview by the author, 4 December 2007.
8. Clausewitz, *On War*, 77.
9. Lt Col James A. Rousseau (507th Electronic Warfare Officer), interview by the author, 4 December 2007.
10. Maj Jon K. Tinsley (USAF Air-Air Weapons System Evaluation Program F-16 Program Manager), e-mail interview by the author, 14 April 2008.
11. Ball, *Fundamentals of Aircraft Combat Survivability Analysis and Design*, 10–12.
12. Ibid., 603.
13. Tinsley, interview.
14. Warden, *Air Campaign*, 66.
15. Hone, "Korea," 467. For a more nuanced view regarding the sanctuary of MiG bases north of the Yalu, see Werrell, "Across the Yalu," 451–75. Dr. Werrell highlights the unassigned raids American pilots took across the Yalu to reduce the strategic sanctuary the communists enjoyed north of the Yalu.

While tactically rewarding, these missions risked global escalation and set a dangerous precedent that supported tactical action over following strategic orders within US Air Force squadrons.

16. Capt Ryan A. Howland (64th Aggressor Squadron/DOO, Mig-29 SME), interview by the author, 3 December 2007

17. Air Force Doctrine Document (AFDD) 2-1.1, *Counterair Operations*, 11.

18. Everett L. Clason (ARCATA Associates Red Flag Analysis Program Manager), interview by the author, 3–5 December 2007.

19. Starting in 2006, adversary threat replication expanded to include the SU-30 and actively guided air-to-air missiles. Thursday scenarios changed to a DCA mission for F-15Cs separated from the remaining Red Flag participants. Other factors affecting the homogeneity of the simulation, such as a more complete and active Red Force increased the level of training "fog" in the scenario. Future classified analysis of the post-2006 results may be extremely useful but is beyond the scope and classification of this thesis.

20. Hugh H. Lester (ARCATA Associates Night Air-Air Mission Analyst), interview by the author, 3–5 December 2007.

21. Don Newell (ARCATA Associates Day Air-Air Mission Analyst), interview by the author, 3–5 December 2007.

22. Imonti, interview.

Chapter 3

Results

We will need those extra planes because this is an aerial war in which one or the other of the combatants will be driven from the sky — and it won't be us. This is a grim struggle in which anything goes. . . . The only thing that counts is the score. Did you kill the enemy or did he kill you?

—Lt Gen Henry H. Arnold
"Our Air Force after One Year at War"

The regression models built in chapter 2 are of little value unless they can help shape operational plans and inform strategic decisions. To be useful, the model must answer vital questions that shape an air campaign and more specifically the air superiority campaign against enemy aircraft. What is the enemy's most dangerous course of action? How much mass is needed to accomplish the objective? Will more aircraft increase the chances of success? If more aircraft will help, how much of an advantage will they provide? These questions frame the essential elements of the initial air campaign plan.

Once the plan is enacted, the commander also needs a method to inform him of the ramifications of actual events and to illuminate decision points for greater advantage. Are the plan's assumptions valid? Is there a better plan for defeating the actual enemy course of action? How long will it take before we are ready to enter the next phase of execution? Do we need reinforcements, and if so, how many? What is the potential effect of a new enemy technology on the battlefield? Anticipating the answers to these questions can avert battlefield disaster by keeping operations short of a culminating point. Additionally, correctly assessing the tide of war and making the appropriate adjustments stands at the core of the operational art.

Bounding these operational questions are strategic decisions about numbers and types of aircraft made years or even decades before a confrontation erupts. Between the end of World

War II and the demise of the Soviet Union, American defense policy focused on opposing the gigantic Soviet threat and averting global catastrophe.[1] This emphasis was obviously unavoidable based on the perceived menace of Communism and the immense size of the Soviet military. Today's reality, however, requires a different balance between both fiscal responsibility and a ready and capable force structured for victory against a robust opponent. Therefore, a better understanding of the requirements is essential to ensure an adequate strength to meet the nation's grand strategy but at minimum cost. Finding a method for understanding the relationships is essential for enhancing the decision process. The following pages present one method of organizing the information and augmenting a commander's understanding of aerial warfare before the first combat sortie launches.

Operational Use

Taken individually, the regression lines of both the F-15C and Red Air provide little relevant insight. In fact, they appear to be both banal and a confirmation of obvious conventional wisdom. Insinuating that adding more aircraft to a mission decreases Blue losses and increases Red losses is common sense and requires no further discussion. Plotting the lines together, however, proves powerful in augmenting the understanding of aerial combat. Figure 16 plots both lines together with the scatter chart data and 95 percent confidence intervals.

Before proceeding further, understand the importance of each chart element. The X-axis plots force ratio on a logarithmic scale, and the Y-axis represents expected attrition rate between 0 and 100 percent. The areas in gray indicate the regions not represented by Red Flag data and are therefore only extrapolations of observed trends. Future graphs will continue to include this feature to emphasize which regions of the graphs represent actual data. It is also essential to emphasize that although future graphs will indicate the regression line only, they do not represent the only possible result from any single engagement. Instead, the regression lines represent the averaged peaks of the individual bell curves for each force ratio. As an

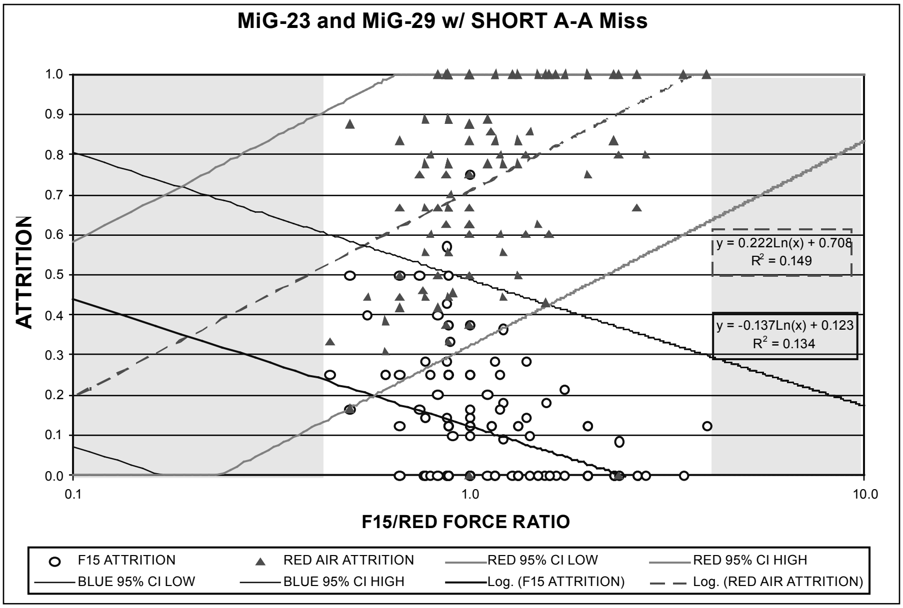


Figure 16. MiG-23/29 short attrition lines log scale.

example, figure 17 represents the distribution of points at an even 1.0 force ratio.

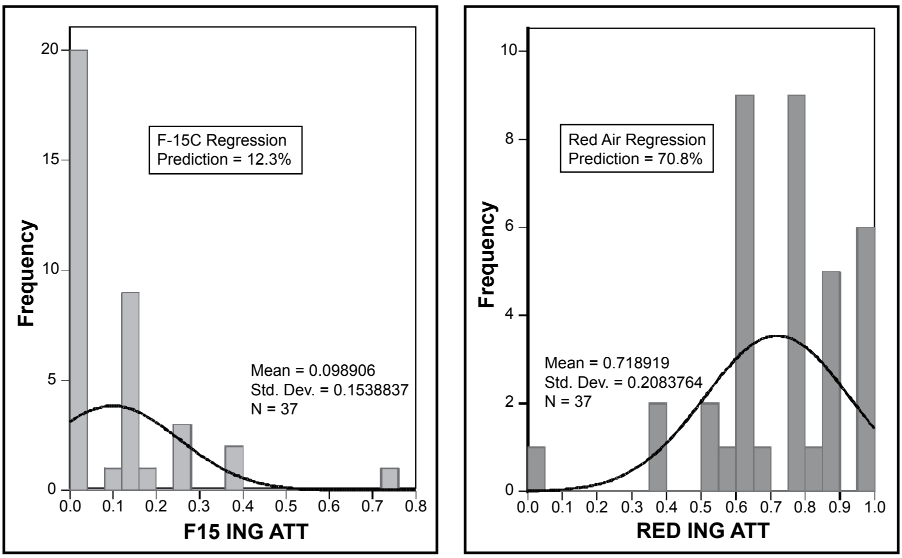


Figure 17. 1:1 (1.0) Force ratio histogram.

Therefore, remember in subsequent charts that there will be deviations from the regression line for individual missions. Over time, however, the averages of several missions will move closer toward the regression line. As emphasized in chapter 1 during the discussions of Lanchester's method, there is clarity with deterministic solutions that can conceptualize expectations for the commander. Unlike his method, however, this conceptualization adds a view of statistical variability that can further augment a commander's judgment about the amount of risk the plan accounts for and even how the battle is progressing.

Remember that figure 16 represents a combination of three different values that prove helpful in calculating most of the information needed for analyzing an air superiority campaign. Each of the attrition lines (B_{att} and R_{att}) represents the expected losses for each side divided by the total number of sorties where the variables B and R indicate F-15C and Red Air respectively.

$$B_{att} = \frac{B_{loss}}{B_{total}} \tag{1}$$

$$R_{att} = \frac{R_{loss}}{R_{total}} \tag{2}$$

The force ratio (F_{rat}) represented on the X-axis is the ratio of Blue sorties to Red sorties.

$$F_{rat} = \frac{B_{total}}{R_{total}} \tag{3}$$

With this in mind, the graph represents the interaction of the two competing weapon systems, all Blue losses (B_{loss}) represent Red kills (R_{kill}), and Red losses (R_{loss}) represent Blue kills (B_{kill}). Therefore, attrition equations 1 and 2 can be modified as the following:

$$\begin{aligned} B_{att} &= \frac{B_{loss}}{B_{total}} = \frac{R_{kill}}{B_{total}} \\ R_{att} &= \frac{R_{loss}}{R_{total}} = \frac{B_{kill}}{R_{total}} \end{aligned} \tag{4}$$

Dividing R_{att} by B_{att} results in the attrition ratio (A_{rat}) for each force ratio. By simplifying the factors using the refined values

for attrition taken from equation 4, attrition ratio equals the following:

$$A_{rat} = \frac{R_{att}}{B_{att}} = \frac{\dfrac{B_{kill}}{R_{total}}}{\dfrac{R_{kill}}{B_{total}}} = \left(\frac{B_{kill}}{R_{kill}}\right)\left(\frac{B_{total}}{R_{total}}\right) \qquad (5)$$

Since kill ratio (K_{rat}) is the number of Blue kills divided by Red kills,

$$K_{rat} = \frac{B_{kill}}{R_{kill}} \qquad (6)$$

further simplification of equation 5 results in the realization that the attrition ratio equals kill ratio (equation 6) times force ratio (equation 3).

$$A_{rat} = \left(\frac{B_{kill}}{R_{kill}}\right)\left(\frac{B_{tot}}{R_{tot}}\right) = K_{rat} F_{rat} \qquad (7)$$

Therefore, kill ratio equals attrition ratio divided by force ratio.

$$\therefore K_{rat} = \frac{A_{rat}}{F_{rat}} \qquad (8)$$

As identified in chapter 1, kill ratio is an important operational measure of merit for assessment. Plotting kill ratio from the attrition lines results in a line with a sideways S pattern as shown in figure 18. The secondary axis to the right side of the graph indicates values for kill ratio displayed on a logarithmic scale. Between the force ratios of 0.1 and 0.8, the kill ratio remains nearly constant at approximately five blue kills to one red kill. At an even force ratio of 1:1, the F-15C is winning by an average of 5.8 to one. Once the force ratio reaches 2:1, the F-15C kill ratio reaches 15.4:1. The actual data confirms the predicted trends. In the 24 missions with a force ratio greater than or equal to 2.0, the average kill ratio is 18.4:1. The 22 missions

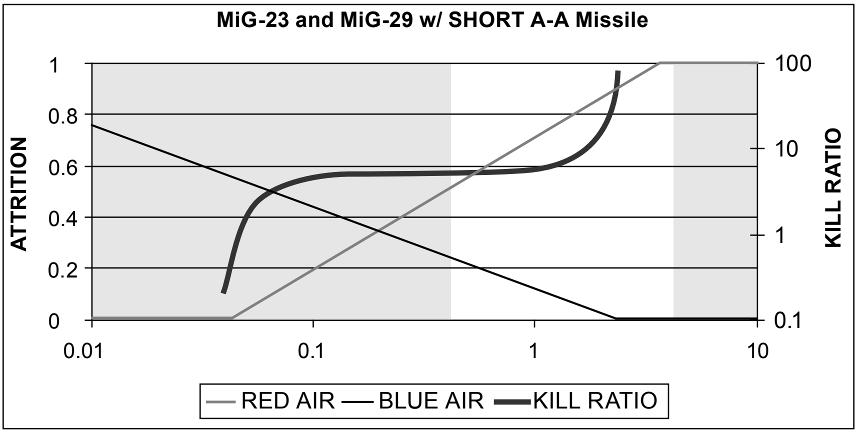


Figure 18. MiG-23/29 short kill ratio.

with a force ratio less than or equal to 0.8 indicate a kill ratio of only 4.5:1.

The shape of the kill ratio curve in this study suggests the presence of three regions of aerial combat that require different strategies. The first region, decisive air superiority, consists of the region where kill ratio is on the dramatic increase. Assuming the data used in the analysis is reasonably close to actual conditions, commanders could expect a high kill ratio with disproportionate enemy losses and a rapid establishment of air supremacy. For this scenario, force ratios greater than 1.0 are a good starting place, with a peak kill ratio of 73:1 at the force ratio of 2.47, where F-15C attrition approaches zero. After that point, inefficiency starts to decrease the kill ratio slightly due to the increased number of aircraft exposed to the risk of combat without the ability to increase the toll on enemy forces. The decrease in kill ratio passed the 2.47 force ratio is, however, insignificant compared to the benefit of overwhelming enemy forces. As a result, larger force ratios would likely add assurance to the outcome by increasing the probability that missions would return with zero losses. Unfortunately, larger force ratios would also decrease efficiency as the additional sorties generate little excess effect since Red attrition is already near 100 percent.

The second region, numeric attrition, is captured by the flat kill ratio plateau between the force ratio of 0.1 and 1.0. Incremental adjustments in the force ratio within this region will have little or no observable effect on the kill ratio between the two sides. If forced to fight in this regime, raw numbers, morale, and the industrial base to produce more aircraft become the deciding factor in victory. Arguably, this region describes most combat experiences, especially early in a campaign when forces are fresh. Once attrition starts, the physical realities of the interaction between the forces bind a commander's options. Additionally, factors like tactical and technological change become significant in determining the campaign's outcome since they may shift the attrition rate more significantly than small changes in the force ratio. The next section explores the effects of new technology on the battlefield in more detail, but it is important to emphasize its potential here.

The third region, desperate measures, exists on the descending curve of enemy superiority. With force ratios falling below 0.1, this scenario would result in an exponential loss of aircraft with little return, besides making a show of effort. Within this region, commanders face gigantic strategic problems with maintaining a viable force, let alone gaining air superiority. Depending on the scenario, commanders must choose between making a last valiant stand, piecemealing their forces with little effect, and attempting to shelter their forces for future use.

In addition to kill ratio, a measure of air superiority is also helpful for projecting the follow-on options for the other essential parts of the air campaign. If the initial sweep eliminates most enemy aircraft, following waves of strike aircraft can eliminate the remaining threat and accomplish the air campaign mission without undue reductions in effectiveness. As the number of surviving enemy aircraft increases, however, bomber crews must shift their attention towards survival, and when they do, bombing success will suffer. By anticipating the level of difficulty, planners can efficiently tailor force packages early in the planning process to enable mission success without significant losses or wasted effort. Therefore, the best way to anticipate the level of difficulty for these forces is by calculating the expected number of Red Air surviving the initial sweep, commonly referred to as leakers. The importance of the target will subse-

quently shape the follow-on strike package or even suggest delaying the strike mission until air superiority is sufficient to facilitate the mission without undue risk.

Making this calculation is extremely simple. Since R_{att} is the percentage of enemy aircraft killed in the sweep, subtracting R_{att} from 1 results in the percentage of aircraft surviving as illustrated below.[2]

$$R_{survive} = 1 - R_{att} \tag{9}$$

All that is needed is to determine the number of Red aircraft initially launched. Since US forces cannot control enemy actions, enemy strength is estimated based on F-15C planned sorties and force ratios. In other words, dividing the number of planned F-15C sorties by the force ratio equals the number of enemy sorties for any point on the graph. Figure 19 displays the curves based on the Red Air attrition regression line. The solid line represents the number of leakers anticipated against an eight ship of F-15Cs, and the dashed line to the left represents projected leakers against a four ship. Initially this may seem counter intuitive, but remember the X-axis represents force ratio while the right side Y-axis represents actual aircraft. Therefore, for any force ratio, doubling the number of F-15C also doubles the number of Red Air fighters. To explain this relationship, three scenarios are instructive. First, if eight Red Air are opposed by four F-15Cs, a 1:2 (0.5) force ratio, we

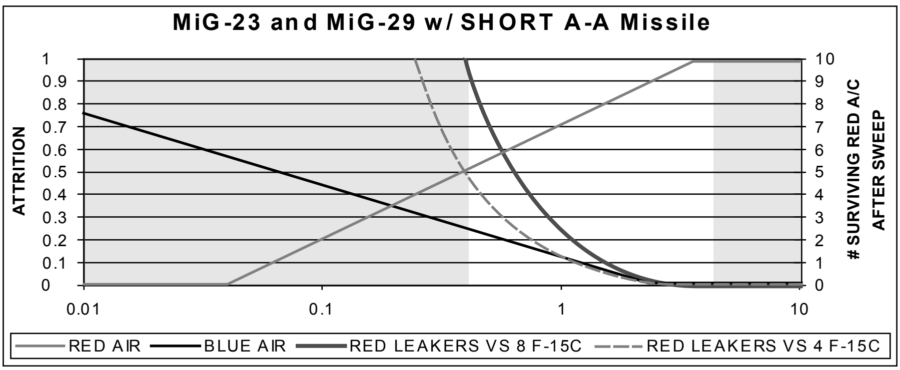


Figure 19. MiG-23/29 surviving Red Aircraft versus F-15C sweep.

would expect about four (3.567 plus or minus error) leakers. If the same eight Red Air are opposed by eight F-15C aircraft, a 1:1 (1.0) force ratio, we would expect about two (2.336 plus or minus error) leakers. Finally, if only four Red Air confront eight F-15Cs, a 2:1 (2.0) force ratio, the result is less than one leaker (0.552 plus or minus error).

Again, these predictions are intuitive, but by quantifying the trend, operational decisions about risk, pacing, force composition, and priority become better defined. Table 1 compares the relevant numbers for each of the three scenarios. The disproportionate difference between the third scenario and the first two clearly emphasizes the advantage of increasing the force ratio.

Table 1. MiG-23/29 campaign plan analysis data.

Force Ratio	Expected F-15C Attrition	Expected F-15C Losses	Expected Red Attrition	Expected Red Losses	Kill Ratio	Red Leakers
4:8 (0.5)	21.8%	0.872	55.4%	4.432	5.1:1	3.567
8:8 (1.0)	12.3%	0.984	70.8%	5.664	5.8:1	2.336
8:4 (2.0)	2.8%	**0.224**	86.2%	3.448	**15.4:1**	**0.552**

Unfortunately, it is impossible to predict the amount of enemy resistance on each mission. Understanding when risks outweigh the rewards, however, can help the commander predetermine specific force ratios to match the acceptable levels of risk (ALR) for each mission. Armed with specific guidance, mission commanders would have better fidelity on when to push to the target, when to proceed with the sweep but call off the strike package, and when to abort the entire mission against unexpected enemy resistance. Thus, the forces could be better prepared to execute in accordance with the commander's intent.

Combining these results also helps to build a more comprehensive picture to educate a commander's perception about an impending war. To explain the application more concretely, an arbitrary force of 100 F-15Cs will provide the backdrop. The following graphs utilize the regression models calculated in appendix B1 to estimate the attrition for each side. As discussed in chapter 1, these calculations use deterministic processing with all of its inherent limitations and pitfalls. Actual results

would vary for each mission and could potentially have significant effects on the viability of the model. Their utility for augmenting a commander's visualization of combat effects, however, outweighs the inevitable inaccuracy of the predictions. As long as the lines remain a planning tool and not a blind prediction of results, they can help shape plans and suggest decision points that would remain ambiguous without the analysis.

Assuming both sides can develop identical UTE rates and on-station times, a direct comparison of aircraft numbers is initially useful as a measure of mass. The following graphs assume a 2.0 UTE rate with one-hour mission (vulnerability) period for each combat iteration unless otherwise noted. The model also assumes aircraft will launch in even numbers. This is typical of Western tactics, but it may not represent every enemy course of action. Additionally, each mission results in a combat engagement and does not account for any effects of OCA-strike missions targeting enemy airfields and supply lines.

Given those assumptions, three outcomes seem probable. First, against an enemy with less than 100 MiG-23 and MiG-29 aircraft, decisive air superiority is a distinct possibility. As noted in figure 20, kill ratios likely would start around 6:1, with the ratio increasing as the enemy's forces are rapidly de-

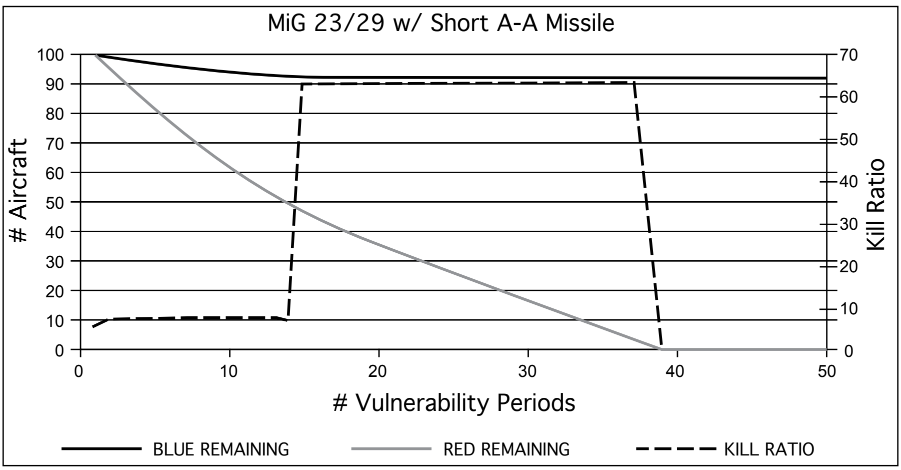


Figure 20. MiG-23/29 short A-A missile 100 versus 100 kill ratio.

stroyed. The changing number of available sorties at the 2.0 UTE rate causes the fluctuating kill ratio. Mission 14 exhibits a dramatic jump in the kill ratio. Once Red Air has less than 48 aircraft available, the aircraft generated per mission drops from four to two. The resulting shift in force ratio produces the sharp change in kill ratio.[3] An enemy surge or switch to three-ship tactics could potentially avert this problem temporarily, but the results would remain similar. Figure 21 also indicates that fewer than two enemy aircraft should survive the initial sweep, so follow-on strike packages would find less resistance en route to their targets. Additionally, after mission 15, only occasional enemy resistance is probable. Even without a successful bombing campaign, gaining air superiority in this scenario would be rapid and complete, whether the enemy chose complete destruction or ceased aerial opposition. Assuming a maximum enemy effort, the enemy would run out of aircraft in 38 missions at the cost of approximately eight F-15Cs.

The second option includes an enemy with more than 100 aircraft and fewer than 500 aircraft. In this regime, initial combat would probably be messy with about one F-15C falling per sweep. Three hundred enemy aircraft provide a snapshot at a potential conflict within this region. The expected kill ratio of

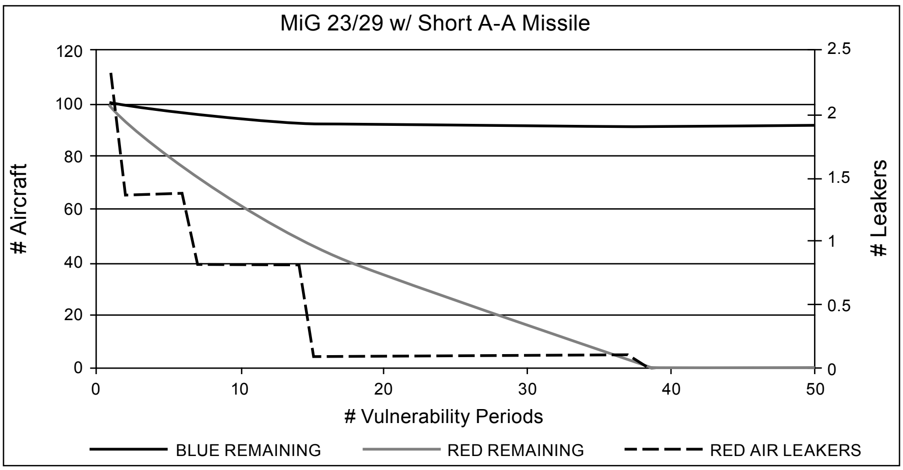


Figure 21. MiG-23/29 short A-A missile 100 versus 100 leakers.

approximately 5:1 displayed in figure 22 would hold for approximately 40 missions. While expected enemy losses outstrip friendly losses and eventually would result in a Blue numerical advantage, the resulting losses of F-15Cs would prove significant. Additionally, as numbers fall, the peak kill ratio would only reach approximately 15:1 after the 44th mission.

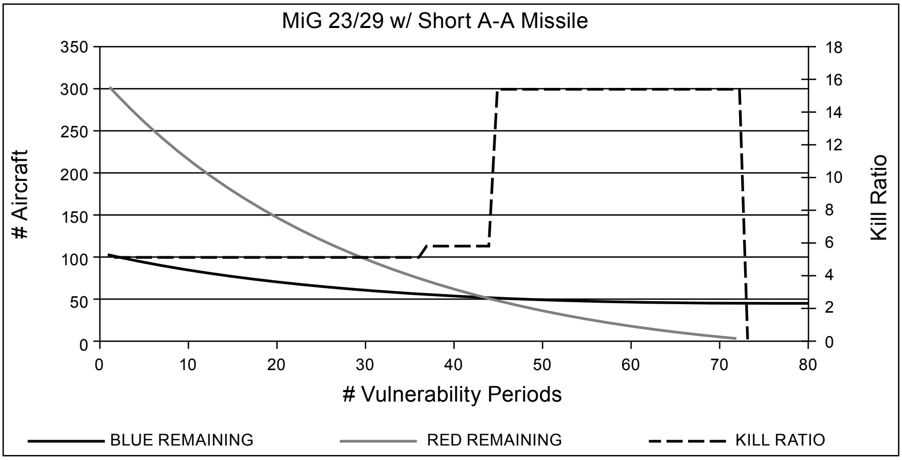


Figure 22. MiG-23/29 short A-A missile 100 versus 300 kill ratio.

Expected losses of 52 F-15Cs in 73 missions could prove catastrophic for American morale. Furthermore, if the combat progressed at a full pace, only three days would elapse from start to finish. This would offer virtually no time for reinforcements, without a sanctuary or cease-fire. Finally, figure 23 explains the limitations on air superiority during the early phases of the war. Leakers would only drop below four on the 30th mission and below two after 36 iterations. This could delay the follow-on bombing effort, especially if the number of available aircraft is limited or vulnerable to attack. More significantly, those follow-on missions could only proceed in safety after the majority of F-15C losses had already taken place. As a result, the strategic flexibility for supporting future combat operations could also decrease.

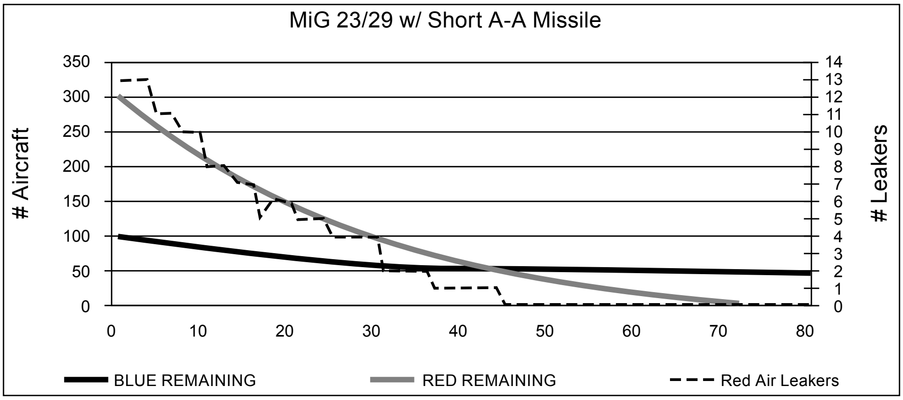


Figure 23. MiG-23/29 short A-A missile 100 versus 300 leakers.

Finally, the third scenario with more than 500 enemy aircraft indicates a region of potential defeat without changes in technology or tactics. Figure 24 depicts the mean results of 100 F-15Cs against an armada of 600 MiG-23/29 type fighters. Consistently outnumbered, the F-15Cs would face a swarm of other lesser aircraft to rely solely on mass to offset the F-15C's technological advantage. In approximately 80 missions, the enemy

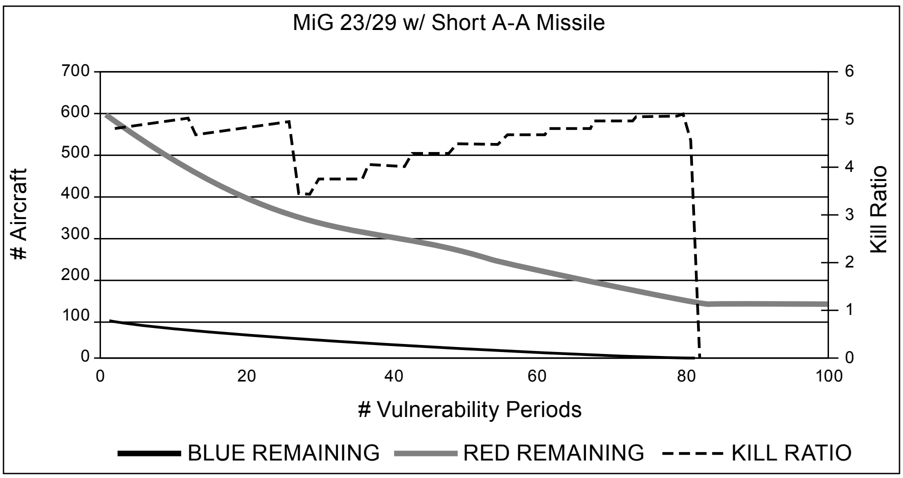


Figure 24. MiG-23/29 short A-A missile 100 versus 700 kill ratio.

would own air superiority with all 100 F-15Cs destroyed and about 140 enemy fighters remaining. Additionally, few if any Blue Air bombing missions are possible in such a scenario because of the overwhelming numbers of enemy aircraft still defending the area.

Admittedly, this is a glaring oversimplification of an operational scenario, but it is necessary to highlight the basic math. This scenario also provides the opportunity to discuss the ability of other aircraft to augment the F-15C forces during the sweep. Current multirole fighters from both the Air Force and Navy can aid in the sweep mission if necessary. Red Flag tactics often use an additional four ships of fighters for just this purpose. Unfortunately, due to airspace congestion, limited tactical integration, or technical limitations, the other conventional sweep aircraft account for an overall kill ratio of 2.1:1 while the F-15C accounts for 5.8:1 against the MiG-23/29 combination with the short air-to-air missile (fig. 25). At the same time, F-15C attrition averaged 10.1 percent, while other aircraft accounted for only 4.2 percent.[4] Based on the author's experience at Red Flag and the data, F-15Cs do the majority of the high-threat work and the augmenting aircraft cover other areas with less threat. This study's limited focus and data fidelity also inhibited a positive correlation between augmentation and

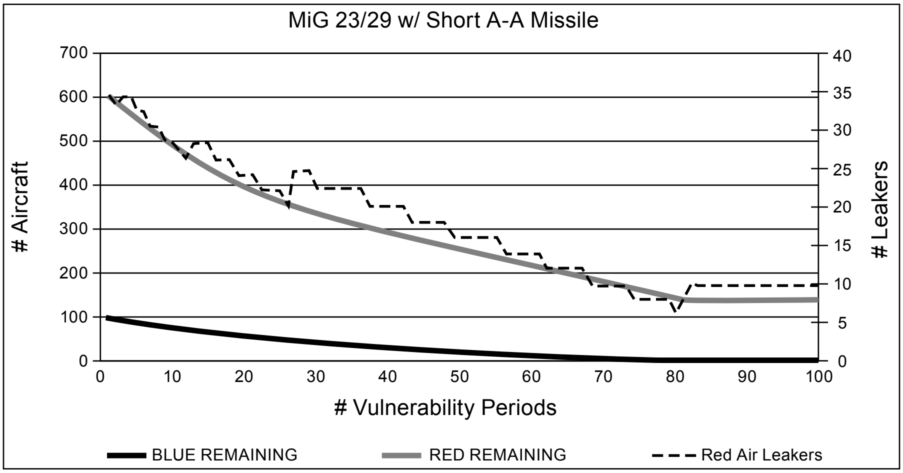


Figure 25. MiG-23/29 short A-A missile 100 versus 700 leakers.

changes in kill ratio. Future studies are therefore needed to reach any conclusions about the effectiveness of this tactic.

Finally, depending on the scenario, modifying the standard 24-hour operations pattern could prove helpful, especially when force ratios are close to the transition from the middle ground of attrition to decisive air superiority. For example, if forces on both sides were approximately equal, redistribution of sorties to favor specific missions could improve overall effects by temporarily spiking the kill ratio and providing better protection of bomber assets. This method could facilitate earlier bombing missions by massing sweep assets to defend and overwhelm the defense's capabilities. Similarly, by temporarily increasing the UTE rates, commonly referred to as a surge, the aircraft sorties could boost the force ratio into the decisive air superiority regime, but not without risk. If the desired enemy attrition rates do not materialize, the gamble could prove counterproductive. Once aircraft cross the threshold of declining maintenance standards, available sorties will decrease despite planned efforts to increase the UTE rate. The result could be a chaotic operational effort instead of a measured plan for action.

Effects of New Enemy Technology

Some technological innovations can significantly alter the balance of power between two military forces. Changing the scenario from the MiG-23/29 to the SU-27 represents more than a new tactical problem. The added capability of the new aircraft and missile also makes the operational problem of defeating the better-equipped enemy more challenging, especially if the goal is decisive air superiority. Figure 26 initially looks similar to the previously explained figure 16, but closer inspection reveals a few differences. First, the 95 percent confidence intervals are farther apart. This is likely due to the smaller data set rather than any correlation with the new technology. Second, the data set contains less diversity in the force ratio than the previous data set. Therefore, extrapolation of the data begins earlier than in the previous example. Fortunately, the data trends closely mirror the earlier results, so they appear reasonable.

Calculating the expected kill ratio for the SU-27 begins to highlight the added difficulty of this scenario. Figure 27 indi-

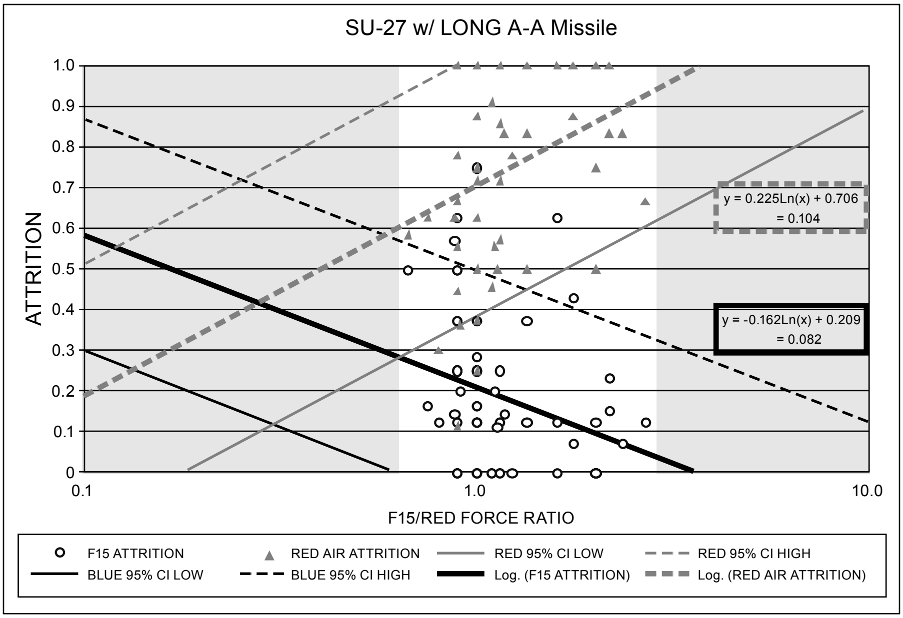


Figure 26. SU-27 long missile attrition lines log scale.

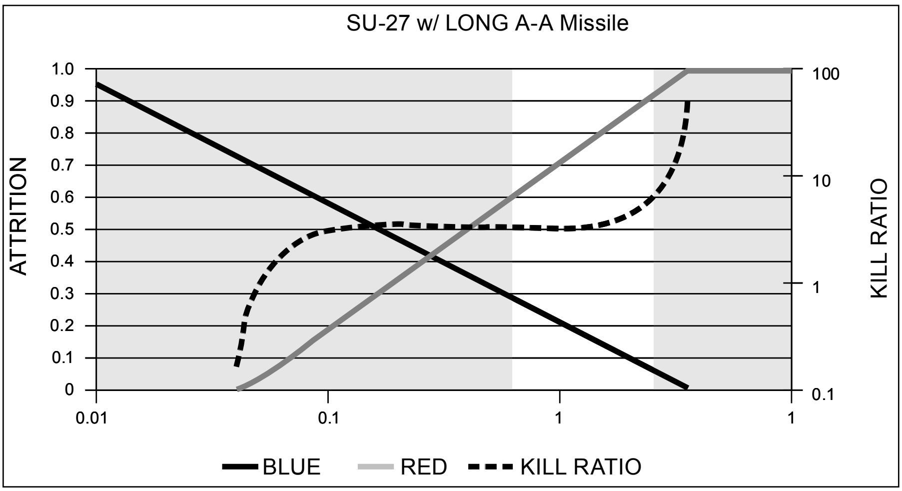


Figure 27. SU-27 long kill ratio.

cates that the three regions of air superiority discussed in the MiG-23/29 scenario are still present, but their values have changed. The first region, decisive air superiority, does not begin until approximately 2.0 and stretches toward peak attrition at a force ratio of 3.5. The second region, numeric attrition, is obviously wider, ranging from 0.1 to 2.0. More significant is the average kill ratio in the center plateau of only 3.5:1. Finally, the third region, desperate measures, remains virtually identical to the lesser threat. The reason for the shift is more obvious by plotting both combinations together in figure 28. Red Air attrition shifted hardly at all between the two cases. As a result, the number of leakers expected for any force ratio remains identical to those predicted in figure 19. Based on data and experience at Red Flag, it is difficult to draw specific inferences from this lack of change, but there are two likely options. First, it could simply be a matter of chance, but given the quantity of data, it is unlikely that both the slope and intercept would remain the same. Second, none of the relevant factors relating to the Red Air attrition changed; therefore, a constant attrition model is expected. The aircraft simulating both threat systems remained identical. Similarly, the replicated defensive tactics

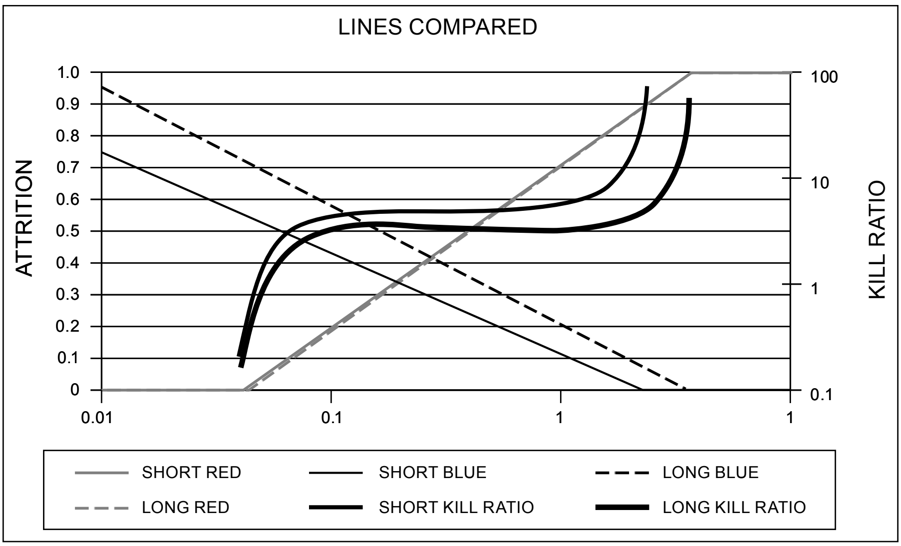


Figure 28. Combined attrition and kill ratio.

for both aircraft and missile combinations are virtually identical. In conclusion, the capabilities and tactics of the F-15C remained constant. Therefore, it is possible that target aircraft attrition is driven by the defensive systems' interaction with enemy offensive weapons.

As expected, F-15C attrition increased against the more capable SU-27 and the long-range missile by approximately 9 percent, with a slight increase in the slope of the line. As noted earlier, the slope is somewhat questionable due to the narrow range of the data. The number, however, correlates closely to the final weapons T-test indicating an overall difference in attrition between the two groups of 7.7 percent (p=0.002) in appendix A12. The increase in F-15C attrition causes the resulting drop in the kill ratio. The most significant change, however, is the F-15C zero attrition point shift to the right. That move requires a significant increase in the forces required to approach increasing returns on attrition as indicated in figure 24. Instead of achieving an expected kill ratio of 15.4:1 with a 2.0 force ratio, the SU-27 threat would likely yield a kill ratio of only 4.5:1. Only by expanding the force ratio to 3:1 would the F-15C re-enter the region of decisive air superiority (table 2). As a result, Blue forces face a much higher chance of fighting a lethal war of attrition instead of the decisive battle for air superiority that America and the USAF have grown accustomed to since Operation Desert Storm.

Table 2. SU-27 long campaign plan analysis data.

Force Ratio	Expected F-15C Attrition	Expected F-15C Losses	Expected Red Attrition	Expected Red Losses	Kill Ratio	Red Leakers
4:8 (0.5)	32.1%	1.284	55.0%	4.4	3.4:1	3.600
8:8 (1.0)	20.9%	1.672	70.6%	5.648	3.4:1	2.352
8:4 (2.0)	9.7%	0.776	86.2%	3.448	4.5:1	0.552
12:4 (3.0)	3.1%	0.248	95.3%	3.812	10.3:1	0.188

As a result, the operational decisions possible in the MiG scenario become much more restrictive against the better-equipped SU-27. Given the same assumptions and the same

100 F-15C aircraft, the three regions of operational outcomes are still possible, but everything shifts away from the F-15C's advantage. Decisive air superiority is still possible, but only against 50 or fewer SU-27s. The second option also only extends to around 340 enemy aircraft before restrictive losses become a real possibility.

The significant difference between the two scenarios helps to clarify how an apparently small change in weapons technology can affect operational outcomes. The flexibility to request additional forces, however, is only available based on long-term force structure decisions.

Notes

1. Lloyd and Naval War College, *Fundamentals of Force Planning*, 15–16.
2. Ball, *Fundamentals of Aircraft Combat Survivability Analysis and Design*, 22.
3. *Maintenance Metrics U.S. Air Force*, 35. The daily UTE rate is calculated by dividing the number of sorties required by the number of available aircraft. To calculate the number of aircraft required given sorties and the UTE rate, divide the sorties required by the UTE. As an example, to keep four aircraft on station for one-hour vulnerability periods 24 hours a day requires 96 sorties. A 2.0 UTE rate therefore requires 48 aircraft.
4. The F-15C accounted for 1,420 sorties with 143 losses and 829 kills during the ingress portion. The other conventional OCA-sweep players totaled 166 sorties with seven losses and 15 kills.

Chapter 4

Strategic Implications

At the strategic level of war, governments make long-term decisions about force structure and what technologies to procure. On the grand scale, national military force structure is based on the allocation of limited resources and the relationship "among ends, ways, and risk."[1] Clausewitz believed in the power of quality, but he felt the surest method of ensuring success on the battlefield is by striving to "put the largest possible army into the field."[2] Today's defense reality, however, requires a balance between both fiscal responsibility and a constant capability for victory. Colin Gray eloquently framed this dilemma with his question, "How should one resolve disputes between those who urge defense preparation according to threat-based military analysis of what the polity allegedly needs to be secure and those who assert that the polity can only afford to spend so much on defense functions?"[3] Striking the correct balance between essential and desired capabilities is vital for enabling national goals without waste.

Possibly the most important step in the process is defining the military's mission within the national security strategy. Robert Art suggests four categories of military force including defense, deterrence, compellence, and swaggering.[4] Because these functions are independent and overlapping, he concludes, only great nations have the potential to "develop military forces that can serve more than two functions at once. Even then, this is achievable only vis-à-vis smaller powers, not vis-à-vis the other great ones."[5] Understanding the subtle differences between each of the four is essential. Defense requires forces capable of repelling an attack on the nation and minimizing the effects of enemy action.[6] Deterrence is similar to defense because its focus is passive but requires an "institutionalized perception" within the enemy state that military action cannot resolve the conflict.[7] Compellence, by contrast, is necessarily offensive in character. It seeks to induce enemy action by the threat or actual use of military force.[8] Finally, Art's term *swagger* consists of the egoistic display of military prowess through

exercises, demonstrations, or technological expertise.[9] This last category is similar in effect to compellence, but, like defense, it focuses inward by attempting to boost national pride or government legitimacy.[10]

The role of air superiority in each of these realms varies and therefore necessitates a different force structure to enable national objectives. A purely defensive force structure is relatively simple to construct and justify. Using traditional "threat/vulnerability" approaches to defense planning; strategists can simply analyze enemy capabilities and American susceptibility to determine the necessary force structure.[11] Since victory is the only requirement and minimizing the effects is a goal, forces only need to be large enough to prevent decisive enemy action. Therefore, forces sufficient to win within the middle plateau of numerical attrition can assure defense with the minimum economic cost.

While pure defense may appeal to a traditional isolationist, it is inconsistent with America's current role as the global enforcer. Since both deterrence and compellence rely on enemy perceptions for effectiveness, defining force structures becomes more ambiguous. Daniel Byman and Mathew Waxman argue that "will and credibility matter as much as, and often more than, the overall balance of forces."[12] The threshold for success between deterrence and compellence, however, is different due to sunk costs and the need to preserve political face. Since deterrence seeks to avert enemy action before it takes place, adversaries will typically apply a lower threshold for acquiescence because inactive compliance is less attributable to outside influences.[13] Once unacceptable action takes place and compellence becomes necessary, adversaries may calculate the value of their reputation outweighs the risk of confrontation.[14] Consequently, as measured threats of force proceed from deterrence to compellence, credibility also needs to increase and may necessitate the use of force. Therefore, a more proactive foreign policy necessitates a more robust military. Presenting sufficient forces to win within the table of numeric attrition could augment America's deterrent credibility to avert military confrontation, but these forces may not inhibit action by determined foes. If compellent war becomes necessary, the disproportional advantage offered by decisive air superiority will help

to ensure victory with less cost in lives and equipment. Employing forces within this realm also minimizes the time required for victory, which is essential in maintaining public support enabling the political will for action. The costs of maintaining a force large enough to accomplish this, however, are growing rapidly. The combined expense of the ongoing global war on terror with the simultaneous increase in the strength of foreign militaries may make maintaining an undisputed compellence force untenable.

Finally, Art's fourth category, swagger, suggests an entirely different approach to military force structure focused on broad political power instead of pure military clout. From an economic perspective, fielding advanced military hardware can provide significant advantages in the international arena. Mechanisms like embargos, licensing rights, and direct military sales of advanced technology provide the required political capital to influence friends and foes without the threat of violence.[15] Additionally, with swagger's focus on the tool rather than its utility, it is usually enough to field the system only with sufficient numbers to meet the credibility threshold. With this in mind, swaggering offers status and respect "on the cheap."[16] The critical element of this methodology provides the foresight, similar to Pres. Franklin D. Roosevelt's, that enables increased production early enough to influence the air war and avoids a repeat of the blind reverence to technology that hobbled the Luftwaffe in World War II.

This model, besides illustrating the role of force size, highlights the role of technology and stresses the importance acquisition priorities can have on national security. Given the significant shift between the two scenarios shown in figure 29, it is apparent how a longer-range air-to-air missile can affect the overall balance of strength between the two sides. The most important driver for advantage is the point for each side where its attrition approaches zero. This point consistently drives the disproportionate kill ratios on both ends of the graph. The side that can fight closest to this point has a distinct advantage. Comparing the existing kill-ratio curve with a modeled curve for a proposed system makes possible a direct comparison of required numbers.

This added fidelity suggests increasing numbers of current aircraft rather than producing a new system as the most cost-effective strategy. Conversely, if the threat is significant or the new technology is revolutionary and sufficiently affordable, the curves may indicate a compelling reason to transform the force. In either case, this model can help commanders augment their decisions in an intuitive manner. Additionally, the shift of the F-15C attrition line suggests there may be a predictable linkage to focus future efforts. If the interaction between Blue attrition and Red offensive systems exists, logic suggests a similar relationship between Blue defensive systems and Blue attrition exists. Therefore, recent US Air Force emphasis on stealth technology may be logically well founded. The protection stealth provides from attack should negate the advantage of enemy offensive weapons and would therefore enable disproportionate victory with fewer aircraft by shifting the Blue minimum attrition point further left. Further study with testing data is needed to verify the extent of the effect relative to the increased cost.

Recommendations

While potentially interesting, this study is far from complete. The OCA-sweep mission area is an important enabler of airpower, but it is not an end unto itself. Modern surface-to-air threats suggest the need for a similar study of the OCA-SEAD mission area. Similarly, charting success rates for the aircraft putting bombs on target is also essential to building a complete picture of the relationship between mass and technology. To accomplish this, however, each mission area database needs synchronizing to facilitate coherent analysis. To facilitate such an analysis, Arcata data collection should be restructured into the following three blocks. The first of the three, initial sweep, includes all results for all players up to and including the "loss" of the last original Red Air player. The second, ingress, embraces all results after the initial sweep until final weapons release. This includes all OCA-sweep, OCA-SEAD, and Red Air missions until the last striker weapons release. The third, egress, includes all data after weapons release until flights terminate tactical maneuvering. This is not a significant change from most of the current collection, but it does include attempts

to make a better split for the results of the initial sweep from an analytical standpoint.

Enhancing Red Flag's fidelity will also make future analyses more productive. Harnessing NACTS-tracking data to produce real-time computer-generated air-to-air, air-to-ground, and ground-to-air missile fly-out models minimizes the training limitations of the current shot kill mechanism while maximizing data accuracy. Adding new airspace to expand the opportunities for maneuver seems also beneficial. Current initiatives like Red Flag–Alaska are a step in the right direction as long as the quality and quantity of threat replication remains high at the new location. Additionally, varying the numbers of Red Air for each mission may be more productive for altering the threat level than the current system of changing subtle tactical variables. This also allows participants to learn lessons about how variation in enemy numerical strength affects mission viability. These lessons could make the critical difference in averting unneeded combat attrition in future wars.

Finally, the US Air Force must develop a set of operational planning aids to augment current methods. By harnessing DOD's war-gaming infrastructure, a series of charts and graphs similar to those presented in chapter 3 are feasible for virtually any potential scenario. Using stochastic methods, individual scenarios would retain the natural variability of combat, while indicating trends. Additionally, Red Flag and test missions would serve as a verification tool to validate the reasonableness of the overall prediction. Once complete, they would function in the operational level air superiority campaign similar to an energy-maneuverability diagram in tactical level aerial dogfight. By suggesting areas of advantage and vulnerability in relation to the opponent, they would clarify a commander's understanding of the impending battle and help to shape the strategy through understanding.

Notes

1. Lloyd and Castle, *Strategy and Force Planning*, 5.
2. Clausewitz, *On War*, 195.
3. Gray, *Modern Strategy*, 33.
4. Art, "The Four Functions of Force," 153.
5. Ibid., 154.

6. Ibid.
7. Freedman, *Deterrence*, 42.
8. Schelling, *Arms and Influence*, 79–80.
9. Art, "Four Functions of Force," 157.
10. Ibid., 157–58.
11. Lloyd and Castle, *Strategy and Force Planning*, 27.
12. Byman and Waxman, *Dynamics of Coercion*, 18.
13. Schelling, *Arms and Influence*, 82.
14. Jervis, *System Effects*, 387.
15. Baldwin, *Economic Statecraft*, 41–42.
16. Art, "Four Functions of Force," 158.

Chapter 5

Conclusion

This study proposes a model for understanding the relationship between technology, mass, and attrition in aerial warfare that is useful for shaping operational and strategic force decision processes. The F-15C's OCA-sweep mission within Red Flag highlights one potentially useful relationship that has value as a model for air superiority. The change of attrition as force ratios increase is simple to understand and logically feasible. Additionally, the regression line helps to provide a window on the expected variance within a specific scenario. Unfortunately, the character of Red Flag as a tactical exercise and not a test introduces excessive variation into an already chaotic environment. Future analyses should harness the power of computer modeling to minimize the number of variables and produce better representations for operational use. Once complete and validated in such exercises as Red Flag, these diagrams would serve as an operational planning tool. Connecting statistical relationships to the operational art of campaign planning helps to ensure success in campaigns against capable foes.

Most significant, however, this study helps to clarify how kill ratio varies in relation to force ratio and technology. The wide middle area of stability, identified as numerical attrition, is consistent with the traditional notion that kill ratio is largely set by training and technology. It is also consistent with most of the historical record, including the early campaigns of World War II, that suggested little change in kill ratio with nominal changes in the relative mass of forces. This is also the reason technology often produced the only observable change in kill ratio in closely matched forces. From the Fokker scourge of World War I to the need for F-86s during the Korean War, technology altered the balance between victor and vanquished by displacing the attrition lines and thus the kill ratio between the two forces.

The rapid change in attrition rate at either end of the graph caused by changes in force ratios also has great explanatory value in other cases. By indicating regions where an increase in

mass dictates a lop-sided victory, the concept accounts for several notable cases in the historical record. Primary among these cases is the previously discussed rapid change in kill ratio during the aerial assault on Germany. Doubling the force ratio during mid-1944 resulted in a sixfold increase in kill ratio in only three months. While the increase in force ratio is not the sole reason for the change, the correlation is strikingly similar to the Red Flag data. The uneven air supremacy enjoyed in Operations Desert Storm and Allied Force also closely mirrors the decisive air superiority regime predicted by the model. In both cases, the US Air Force fought within the region of decisive air superiority due to its overwhelming mass and technology. This advantage may prove transient, however, because, similar to Wall Street, "past performance does not predict future returns." Adversaries will attempt to balance America's advantage with their own unique combination of mass and technology.

Before the next major war begins, strategic decisions about military force structure will shape the feasibility of operational plans and preordain the costs in both the dollars and lives required for victory. The F-22 is already superseding the F-15C with increased capability and reduced numbers. The joint strike fighter will similarly supplant the F-15E, F-16, and A-10 in the next decade. At first glance, this change should guarantee aerial dominance in the future through technology. Unfortunately, the disproportionate advantage afforded by stealth and fifth-generation technology remains too expensive and complex to field in large numbers. These shrinking inventories of high-technology aircraft will likely result in a conflict where America will fight outnumbered and completely reliant on technology to maintain a preponderance of strength.

The danger, however, is in dropping forces too low without moderating expectations. While these new systems may have the ability to strike the same number of targets as their more numerous predecessors, their dwindling numbers can cause other problems. Smaller numbers amplify the effects of fog and chance. With the study's regression calculations, outliers defied the averages: missions where bad days conspired with possibility to produce unexpected losses. Over thousands of sorties, these anomalies did not have a significant impact on the outcome. As the numbers decrease, however, single events grow

in meaning. The recent accidental crash of a B-2 is a perfect example. The loss of a single, irreplaceable aircraft will have long-term effects on strategic options, especially when victory requires maximum effort.

Imagine the effect upon the inventory the first time an enemy reveals the capability to detect, target, and kill American stealth platforms with lethal regularity. If timed appropriately, the quick succession of losses could prove more damaging than Pearl Harbor by significantly reducing the number of available aircraft. Foreign aviation technology is developing at a rapid pace. Soon another military might balance the overwhelming advantage of the US Air Force. The essential problem lies in identifying the challenge before a confrontation erupts. The strategic insight provided by this model could help to identify the limitations of the force early enough to enable a timely correction. In some cases, a simple transition from an overt policy of compellence to a more conciliatory swaggering or defensive posture may save limited funds for other necessities. In other more dire situations, early recognition will build the requisite time for either producing additional aircraft or trading up for more technology.

Silver bullets seldom manifest themselves in warfare. When they do appear, their lop-sided effectiveness is usually fleeting as the enemy adapts to the new tactics or technology. America's aerial dominance, enabled by stealth and precision, is a transitory advantage with a finite duration. The inevitable rebalancing of military capability will force a return to inventory comparisons and small incremental changes in technologies, countertactics, and organizations. America can minimize its risk of falling victim to hubris by anticipating the impending enemy changes and planning for them. By avoiding the pitfall of assuming future disproportionate advantages and planning for parity, the Air Force can avoid defeat in the next war. Understanding the relationship between mass and technology is the best way to offset the impending rebalance of global military force. By returning to brutal honesty and strategic introspection, the Air Force can identify its weaknesses and be ready to win the next war.

Appendix A

Data Set Variance

A1. Year Attrition Analysis of Variance (ANOVA) 2001–2005

Author's original work using Statistical Program for the Social Sciences (SPSS) 12.0.1

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
F15_ING_ATT	2001	72	.177083	.1409508	.0166112	.143962	.210205	.0000	.6250
	2002	92	.133742	.1578904	.0164612	.101043	.166440	.0000	.6250
	2003	47	.125532	.1671652	.0243835	.076450	.174613	.0000	.7500
	2004	54	.089267	.1383443	.0188263	.051506	.127027	.0000	.7500
	2005	34	.105252	.1443346	.0247532	.054891	.155613	.0000	.5000
	Total	299	.131616	.1525829	.0088241	.114251	.148981	.0000	.7500
OCA_ING_ATT	2001	74	.154636	.1192056	.0138574	.127018	.182254	.0000	.5000
	2002	93	.123534	.1383595	.0143472	.095039	.152028	.0000	.5000
	2003	47	.123759	.1673870	.0244159	.074612	.172906	.0000	.7500
	2004	59	.091821	.1363615	.0177528	.056285	.127357	.0000	.7500
	2005	34	.105252	.1443346	.0247532	.054891	.155613	.0000	.5000
	Total	307	.122946	.1399754	.0079888	.107226	.138666	.0000	.7500
RED_ING_ATT	2001	74	.569337	.2307686	.0268263	.515873	.622802	.0000	1.0000
	2002	93	.748192	.1909472	.0198003	.708867	.787517	.2500	1.0000
	2003	47	.770652	.1967436	.0286980	.712886	.828418	.3750	1.0000
	2004	59	.784759	.2209083	.0287598	.727190	.842328	.0000	1.0000
	2005	34	.766667	.1957723	.0335747	.698358	.834975	.5000	1.1250
	Total	307	.717593	.2236921	.0127668	.692471	.742714	.0000	1.1250

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	.511	4	294	.728
OCA_ING_ATT	.596	4	302	.666
RED_ING_ATT	.562	4	302	.690

ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.271	4	.068	2.993	.019
	Within Groups	6.666	294	.023		
	Total	6.938	298			
OCA_ING_ATT	Between Groups	.142	4	.036	1.834	.122
	Within Groups	5.853	302	.019		
	Total	5.995	306			
RED_ING_ATT	Between Groups	2.194	4	.548	12.627	.000
	Within Groups	13.118	302	.043		
	Total	15.312	306			

Post-Hoc Tests

Multiple Comparisons

Tukey honestly significant difference (HSD) test

Dependent Variable	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_ING_ATT	2001	2002	.0433418	.0236938	.359	-.021692	.108376
		2003	.0515514	.0282378	.361	-.025955	.129058
		2004	.0878166(*)	.0271078	.012	.013412	.162222
		2005	.0718312	.0313343	.150	-.014175	.157837
	2002	2001	-.0433418	.0236938	.359	-.108376	.021692
		2003	.0082096	.0269983	.998	-.065895	.082314
		2004	.0444748	.0258142	.421	-.026379	.115329
		2005	.0284894	.0302221	.880	-.054464	.111443
	2003	2001	-.0515514	.0282378	.361	-.129058	.025955
		2002	-.0082096	.0269983	.998	-.082314	.065895
		2004	.0362652	.0300391	.747	-.046186	.118716
		2005	.0202798	.0339021	.975	-.072774	.113334
	2004	2001	-.0878166(*)	.0271078	.012	-.162222	-.013412
		2002	-.0444748	.0258142	.421	-.115329	.026379
		2003	-.0362652	.0300391	.747	-.118716	.046186
		2005	-.0159854	.0329669	.989	-.106472	.074501
	2005	2001	-.0718312	.0313343	.150	-.157837	.014175
		2002	-.0284894	.0302221	.880	-.111443	.054464
		2003	-.0202798	.0339021	.975	-.113334	.072774
		2004	.0159854	.0329669	.989	-.074501	.106472
OCA_ING_ATT	2001	2002	.0311024	.0216869	.606	-.028414	.090619
		2003	.0308773	.0259672	.758	-.040385	.102140
		2004	.0628153	.0242986	.076	-.003868	.129499
		2005	.0493840	.0288439	.428	-.029773	.128541
	2002	2001	-.0311024	.0216869	.606	-.090619	.028414
		2003	-.0002252	.0249156	1.000	-.068602	.068151
		2004	.0317129	.0231714	.648	-.031877	.095303
		2005	.0182816	.0279009	.966	-.058288	.094851
	2003	2001	-.0308773	.0259672	.758	-.102140	.040385
		2002	.0002252	.0249156	1.000	-.068151	.068602
		2004	.0319380	.0272192	.767	-.042760	.106637

Post-Hoc Tests (continued)

Dependent Variable	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
		2005	.0185068	.0313438	.976	-.067511	.104524
	2004	2001	-.0628153	.0242986	.076	-.129499	.003868
		2002	-.0317129	.0231714	.648	-.095303	.031877
		2003	-.0319380	.0272192	.767	-.106637	.042760
		2005	-.0134313	.0299760	.992	-.095695	.068833
	2005	2001	-.0493840	.0288439	.428	-.128541	.029773
		2002	-.0182816	.0279009	.966	-.094851	.058288
		2003	-.0185068	.0313438	.976	-.104524	.067511
		2004	.0134313	.0299760	.992	-.068833	.095695
RED_ING_ ATT	2001	2002	-.1788551(*)	.0324658	.000	-.267952	-.089758
		2003	-.2013145(*)	.0388735	.000	-.307996	-.094633
		2004	-.2154219(*)	.0363756	.000	-.315249	-.115595
		2005	-.1973294(*)	.0431800	.000	-.315830	-.078829
	2002	2001	.1788551(*)	.0324658	.000	.089758	.267952
		2003	-.0224594	.0372992	.975	-.124821	.079902
		2004	-.0365668	.0346881	.830	-.131762	.058629
		2005	-.0184743	.0417683	.992	-.133100	.096152
	2003	2001	.2013145(*)	.0388735	.000	.094633	.307996
		2002	.0224594	.0372992	.975	-.079902	.124821
		2004	-.0141074	.0407478	.997	-.125933	.097718
		2005	.0039851	.0469224	1.000	-.124785	.132756
	2004	2001	.2154219(*)	.0363756	.000	.115595	.315249
		2002	.0365668	.0346881	.830	-.058629	.131762
		2003	.0141074	.0407478	.997	-.097718	.125933
		2005	.0180925	.0448747	.994	-.105059	.141244
	2005	2001	.1973294(*)	.0431800	.000	.078829	.315830
		2002	.0184743	.0417683	.992	-.096152	.133100
		2003	-.0039851	.0469224	1.000	-.132756	.124785
		2004	-.0180925	.0448747	.994	-.141244	.105059

*The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_ING_ATT

Tukey HSD

Year	N	Subset for alpha = .05	
		1	2
2004	54	.089267	
2005	34	.105252	.105252
2003	47	.125532	.125532
2002	92	.133742	.133742
2001	72		.177083
Sig.		.548	.103

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 53.211.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_ING_ATT

Tukey HSD

Year	N	Subset for alpha = .05
		1
2004	59	.091821
2005	34	.105252
2002	93	.123534
2003	47	.123759
2001	74	.154636
Sig.		.131

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 54.405.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

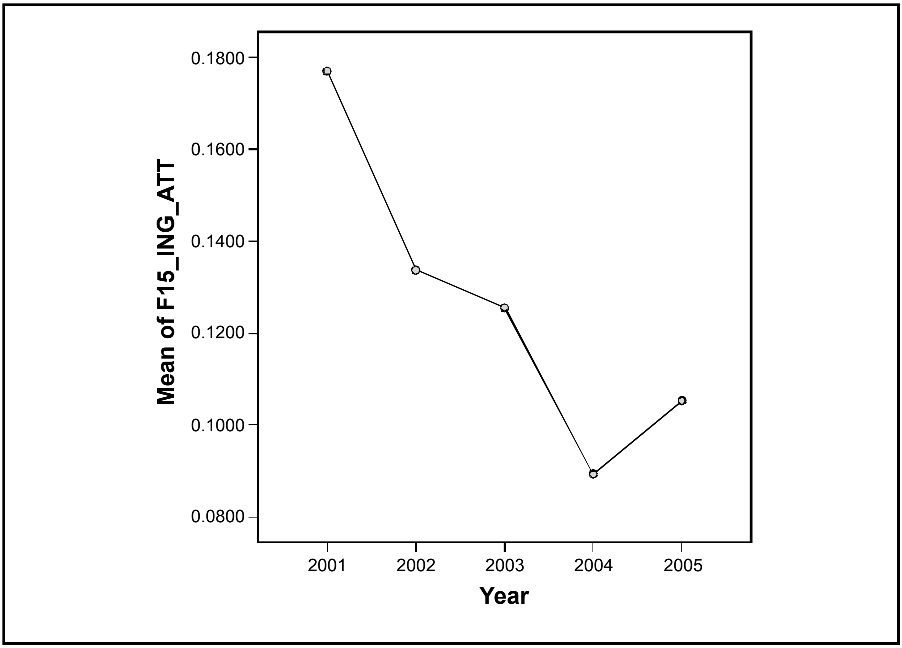
RED_ING_ATT

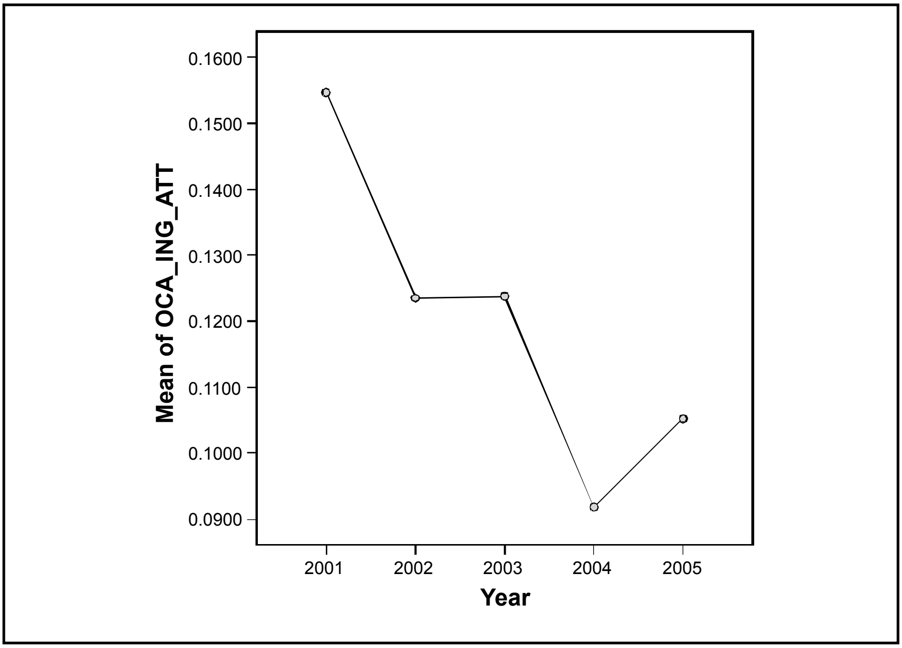
Tukey HSD

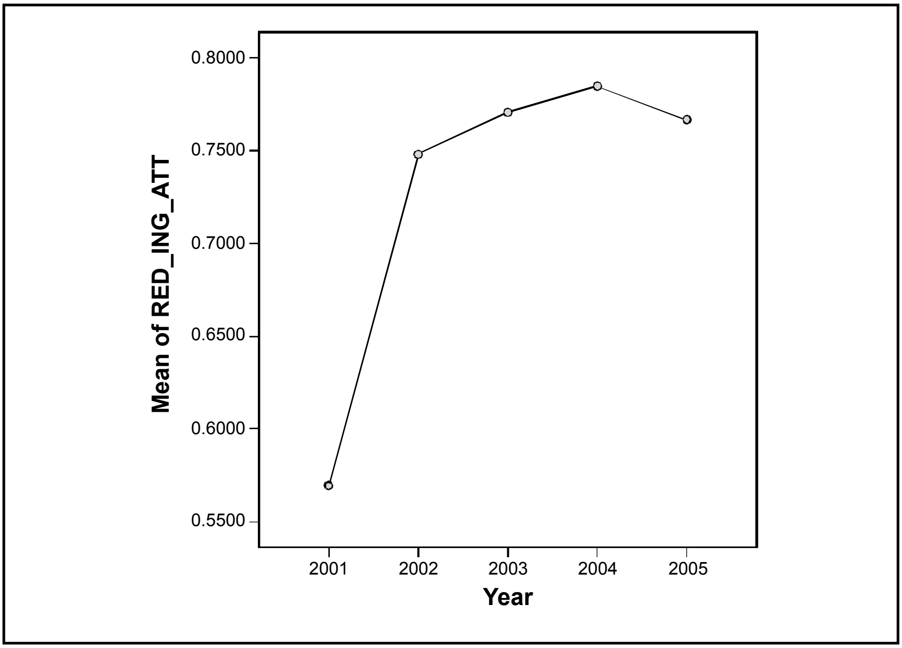
Year	N	Subset for alpha = .05	
		1	2
2001	74	.569337	
2002	93		.748192
2005	34		.766667
2003	47		.770652
2004	59		.784759
Sig.		1.000	.891

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 54.405.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots




0.1600
0.1500
0.1400
0.1300
0.1200
0.1100
0.1000
0.0900
Mean of OCA_ING_ATT
2001
2002
2003
2004
2005
Year


0.8000
0.7500
0.7000
0.6500
0.6000
0.5500
Mean of RED_ING_ATT
2001
2002
2003
2004
2005
Year

Year Force Ratio ANOVA 2001–2005

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
F15_ FLOWN_ RATIO	2001	74	.850290	.2106658	.0244894	.801482	.899097	.0000	1.6000
	2002	93	1.114696	.3389543	.0351479	1.044889	1.184503	.0000	2.6667
	2003	47	1.597357	.8036187	.1172198	1.361406	1.833309	.5556	4.0000
	2004	59	1.363875	.7199627	.0937312	1.176252	1.551499	.0000	2.8000
	2005	34	1.084886	.3197288	.0548330	.973327	1.196444	.6667	2.0000
	Total	307	1.169442	.5596747	.0319423	1.106588	1.232297	.0000	4.0000
FLOWN_ RATIO	2001	74	1.044235	.3277100	.0380955	.968311	1.120160	.4444	2.4000
	2002	93	1.405164	.4664773	.0483714	1.309094	1.501234	.8889	3.5000
	2003	47	1.824308	1.3103846	.1911392	1.439564	2.209051	.5556	6.0000
	2004	59	1.502051	.5958926	.0775786	1.346761	1.657342	.4444	2.8000
	2005	34	1.084886	.3197288	.0548330	.973327	1.196444	.6667	2.0000
	Total	307	1.365483	.7054171	.0402603	1.286261	1.444705	.4444	6.0000
OCA_ F15_FL	2001	72	7.74	1.256	.148	7.44	8.03	4	10
	2002	92	8.62	1.518	.158	8.31	8.93	4	12
	2003	47	7.83	.524	.076	7.68	7.98	5	8
	2004	54	9.59	2.904	.395	8.80	10.39	4	14
	2005	34	7.12	1.343	.230	6.65	7.59	4	8
	Total	299	8.29	1.851	.107	8.08	8.50	4	14
OCA_ TOT_ FTR_FL	2001	74	9.08	2.052	.239	8.61	9.56	4	12
	2002	93	10.54	1.862	.193	10.15	10.92	4	14
	2003	47	8.43	1.543	.225	7.97	8.88	5	12
	2004	59	9.46	2.920	.380	8.70	10.22	4	14
	2005	34	7.12	1.343	.230	6.65	7.59	4	8
	Total	307	9.28	2.312	.132	9.02	9.54	4	14
RED_ TOT_ FTR_FL	2001	74	9.04	1.763	.205	8.63	9.45	4	13
	2002	93	7.94	1.673	.174	7.59	8.28	3	11
	2003	47	5.89	2.189	.319	5.25	6.54	2	9
	2004	59	6.76	1.775	.231	6.30	7.23	4	10
	2005	34	6.82	1.487	.255	6.30	7.34	4	9
	Total	307	7.54	2.079	.119	7.31	7.77	2	13

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_FLOWN_RATIO	33.964	4	302	.000
FLOWN_RATIO	20.181	4	302	.000
OCA_F15_FL	41.497	4	294	.000
OCA_TOT_FTR_FL	16.740	4	302	.000
RED_TOT_FTR_FL	5.622	4	302	.000

ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
F15_FLOWN_RATIO	Between Groups	18.896	4	4.724	18.539	.000
	Within Groups	76.954	302	.255		
	Total	95.850	306			
FLOWN_RATIO	Between Groups	21.455	4	5.364	12.383	.000
	Within Groups	130.815	302	.433		
	Total	152.270	306			
OCA_F15_FL	Between Groups	180.389	4	45.097	15.768	.000
	Within Groups	840.876	294	2.860		
	Total	1021.265	298			
OCA_TOT_FTR_FL	Between Groups	345.171	4	86.293	20.197	.000
	Within Groups	1290.295	302	4.272		
	Total	1635.466	306			
RED_TOT_FTR_FL	Between Groups	361.663	4	90.416	28.426	.000
	Within Groups	960.579	302	3.181		
	Total	1322.241	306			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_ FLOWN_ RATIO	2001	2002	-.2644065(*)	.0786345	.008	-.480206	-.048607
		2003	-.7470677(*)	.0941543	.000	-1.005458	-.488677
		2004	-.5135858(*)	.0881042	.000	-.755373	-.271799
		2005	-.2345960	.1045849	.167	-.521612	.052420
	2002	2001	.2644065(*)	.0786345	.008	.048607	.480206
		2003	-.4826612(*)	.0903413	.000	-.730587	-.234735
		2004	-.2491793(*)	.0840169	.027	-.479750	-.018609
		2005	.0298105	.1011657	.998	-.247822	.307443
	2003	2001	.7470677(*)	.0941543	.000	.488677	1.005458
		2002	.4826612(*)	.0903413	.000	.234735	.730587
		2004	.2334819	.0986939	.128	-.037367	.504331
		2005	.5124717(*)	.1136493	.000	.200581	.824363
	2004	2001	.5135858(*)	.0881042	.000	.271799	.755373
		2002	.2491793(*)	.0840169	.027	.018609	.479750
		2003	-.2334819	.0986939	.128	-.504331	.037367
		2005	.2789898	.1086897	.079	-.019291	.577270
	2005	2001	.2345960	.1045849	.167	-.052420	.521612
		2002	-.0298105	.1011657	.998	-.307443	.247822
		2003	-.5124717(*)	.1136493	.000	-.824363	-.200581
		2004	-.2789898	.1086897	.079	-.577270	.019291
FLOWN_ RATIO	2001	2002	-.3609284(*)	.1025240	.004	-.642288	-.079569
		2003	-.7800723(*)	.1227588	.000	-1.116963	-.443182
		2004	-.4578160(*)	.1148705	.001	-.773059	-.142573
		2005	-.0406503	.1363582	.998	-.414862	.333562
	2002	2001	.3609284(*)	.1025240	.004	.079569	.642288
		2003	-.4191439(*)	.1177872	.004	-.742391	-.095897
		2004	-.0968876	.1095416	.902	-.397506	.203731
		2005	.3202782	.1319002	.111	-.041700	.682256
	2003	2001	.7800723(*)	.1227588	.000	.443182	1.116963
		2002	.4191439(*)	.1177872	.004	.095897	.742391
		2004	.3222563	.1286775	.092	-.030877	.675390
		2005	.7394220(*)	.1481763	.000	.332777	1.146067

Post-Hoc Tests (continued)

Dependent Variable	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	2004	2001	.4578160(*)	.1148705	.001	.142573	.773059
		2002	.0968876	.1095416	.902	-.203731	.397506
		2003	-.3222563	.1286775	.092	-.675390	.030877
		2005	.4171658(*)	.1417100	.029	.028267	.806065
	2005	2001	.0406503	.1363582	.998	-.333562	.414862
		2002	-.3202782	.1319002	.111	-.682256	.041700
		2003	-.7394220(*)	.1481763	.000	-1.146067	-.332777
		2004	-.4171658(*)	.1417100	.029	-.806065	-.028267
OCA_F15_FL	2001	2002	-.883(*)	.266	.009	-1.61	-.15
		2003	-.094	.317	.998	-.96	.78
		2004	-1.856(*)	.304	.000	-2.69	-1.02
		2005	.618	.352	.401	-.35	1.58
	2002	2001	.883(*)	.266	.009	.15	1.61
		2003	.790	.303	.072	-.04	1.62
		2004	-.973(*)	.290	.008	-1.77	-.18
		2005	1.502(*)	.339	.000	.57	2.43
	2003	2001	.094	.317	.998	-.78	.96
		2002	-.790	.303	.072	-1.62	.04
		2004	-1.763(*)	.337	.000	-2.69	-.84
		2005	.712	.381	.336	-.33	1.76
	2004	2001	1.856(*)	.304	.000	1.02	2.69
		2002	.973(*)	.290	.008	.18	1.77
		2003	1.763(*)	.337	.000	.84	2.69
		2005	2.475(*)	.370	.000	1.46	3.49
	2005	2001	-.618	.352	.401	-1.58	.35
		2002	-1.502(*)	.339	.000	-2.43	-.57
		2003	-.712	.381	.336	-1.76	.33
		2004	-2.475(*)	.370	.000	-3.49	-1.46
OCA_TOT_FTR_FL	2001	2002	-1.457(*)	.322	.000	-2.34	-.57
		2003	.656	.386	.435	-.40	1.71
		2004	-.377	.361	.835	-1.37	.61
		2005	1.963(*)	.428	.000	.79	3.14
	2002	2001	1.457(*)	.322	.000	.57	2.34
		2003	2.112(*)	.370	.000	1.10	3.13

Post-Hoc Tests (continued)

Dependent Variable	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
		2004	1.080(*)	.344	.016	.14	2.02
		2005	3.420(*)	.414	.000	2.28	4.56
	2003	2001	-.656	.386	.435	-1.71	.40
		2002	-2.112(*)	.370	.000	-3.13	-1.10
		2004	-1.032	.404	.082	-2.14	.08
		2005	1.308(*)	.465	.042	.03	2.59
	2004	2001	.377	.361	.835	-.61	1.37
		2002	-1.080(*)	.344	.016	-2.02	-.14
		2003	1.032	.404	.082	-.08	2.14
		2005	2.340(*)	.445	.000	1.12	3.56
	2005	2001	-1.963(*)	.428	.000	-3.14	-.79
		2002	-3.420(*)	.414	.000	-4.56	-2.28
		2003	-1.308(*)	.465	.042	-2.59	-.03
		2004	-2.340(*)	.445	.000	-3.56	-1.12
RED_TOT_FTR_FL	2001	2002	1.105(*)	.278	.001	.34	1.87
		2003	3.147(*)	.333	.000	2.23	4.06
		2004	2.278(*)	.311	.000	1.42	3.13
		2005	2.217(*)	.370	.000	1.20	3.23
	2002	2001	-1.105(*)	.278	.001	-1.87	-.34
		2003	2.042(*)	.319	.000	1.17	2.92
		2004	1.173(*)	.297	.001	.36	1.99
		2005	1.112(*)	.357	.017	.13	2.09
	2003	2001	-3.147(*)	.333	.000	-4.06	-2.23
		2002	-2.042(*)	.319	.000	-2.92	-1.17
		2004	-.869	.349	.095	-1.83	.09
		2005	-.930	.402	.143	-2.03	.17
	2004	2001	-2.278(*)	.311	.000	-3.13	-1.42
		2002	-1.173(*)	.297	.001	-1.99	-.36
		2003	.869	.349	.095	-.09	1.83
		2005	-.061	.384	1.000	-1.11	.99
	2005	2001	-2.217(*)	.370	.000	-3.23	-1.20
		2002	-1.112(*)	.357	.017	-2.09	-.13
		2003	.930	.402	.143	-.17	2.03
		2004	.061	.384	1.000	-.99	1.11

* The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_FLOWN_RATIO

Tukey HSD

Year	N	Subset for alpha = .05		
		1	2	3
2001	74	.850290		
2005	34	1.084886		
2002	93	1.114696	1.114696	
2004	59		1.363875	1.363875
2003	47			1.597357
Sig.		.052	.078	.115

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 54.405.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

FLOWN_RATIO

Tukey HSD

Year	N	Subset for alpha = .05			
		1	2	3	4
2001	74	1.044235			
2005	34	1.084886	1.084886		
2002	93		1.405164	1.405164	
2004	59			1.502051	1.502051
2003	47				1.824308
Sig.		.998	.085	.940	.082

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 54.405.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_F15_FL

Tukey HSD

Year	N	Subset for alpha = .05		
		1	2	3
2005	34	7.12		
2001	72	7.74	7.74	
2003	47	7.83	7.83	
2002	92		8.62	
2004	54			9.59
Sig.		.193	.057	1.000

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 53.211.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_TOT_FTR_FL

Tukey HSD

Year	N	Subset for alpha = .05		
		1	2	3
2005	34	7.12		
2003	47		8.43	
2001	74		9.08	
2004	59		9.46	9.46
2002	93			10.54
Sig.		1.000	.072	.053

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 54.405.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

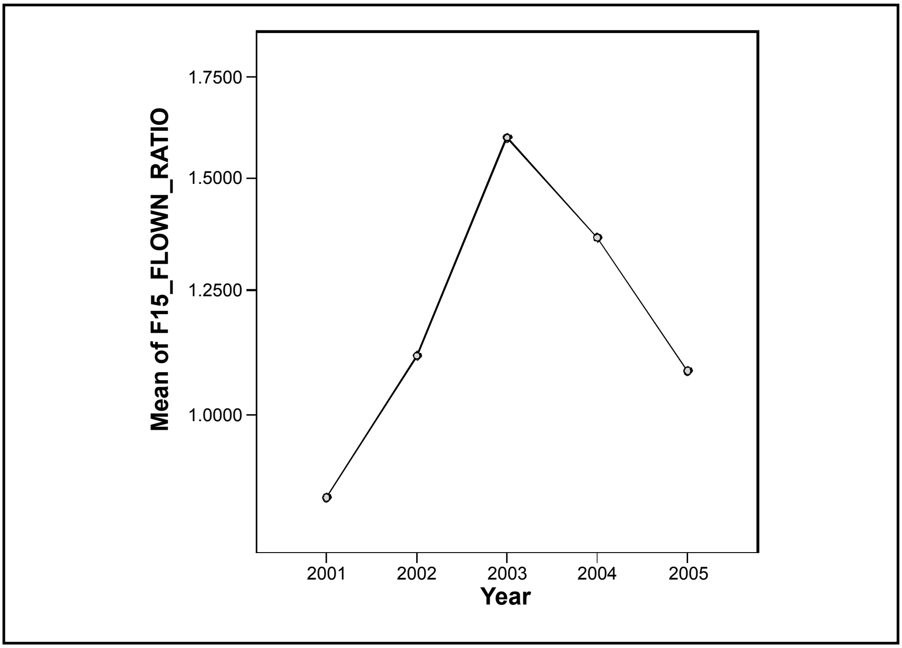
RED_TOT_FTR_FL

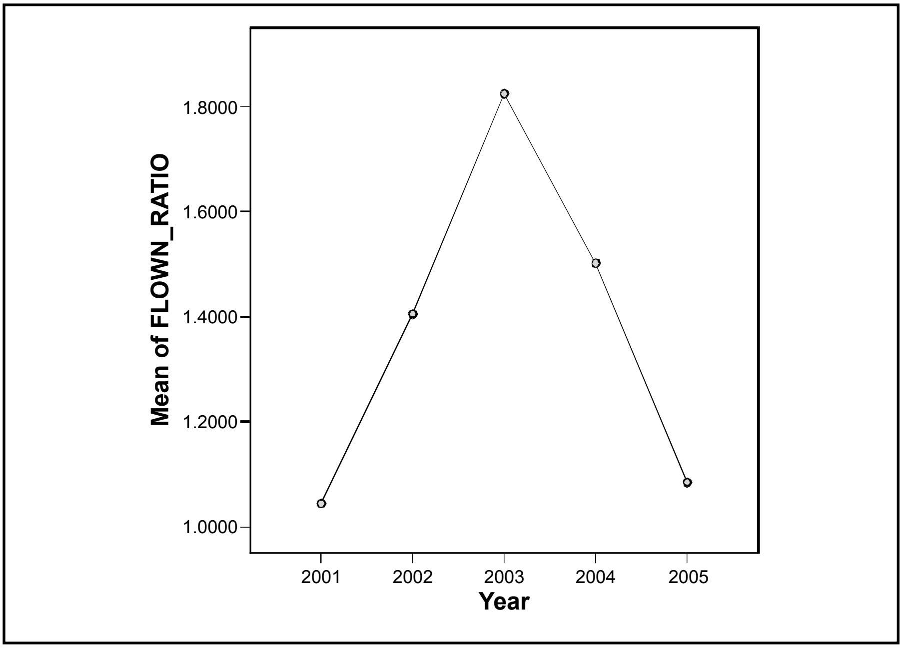
Tukey HSD

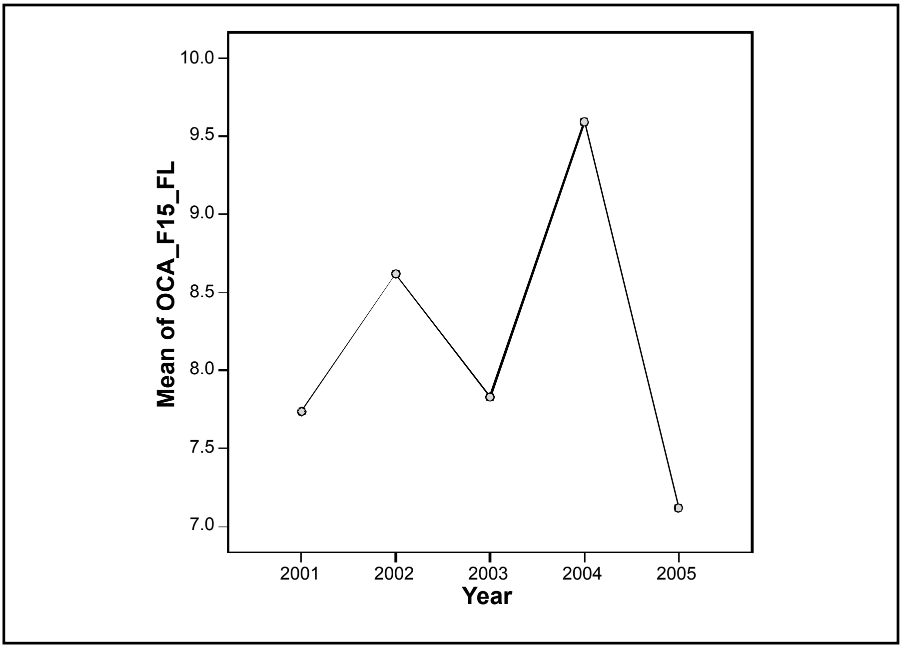
Year	N	Subset for alpha = .05		
		1	2	3
2003	47	5.89		
2004	59	6.76		
2005	34	6.82		
2002	93		7.94	
2001	74			9.04
Sig.		.053	1.000	1.000

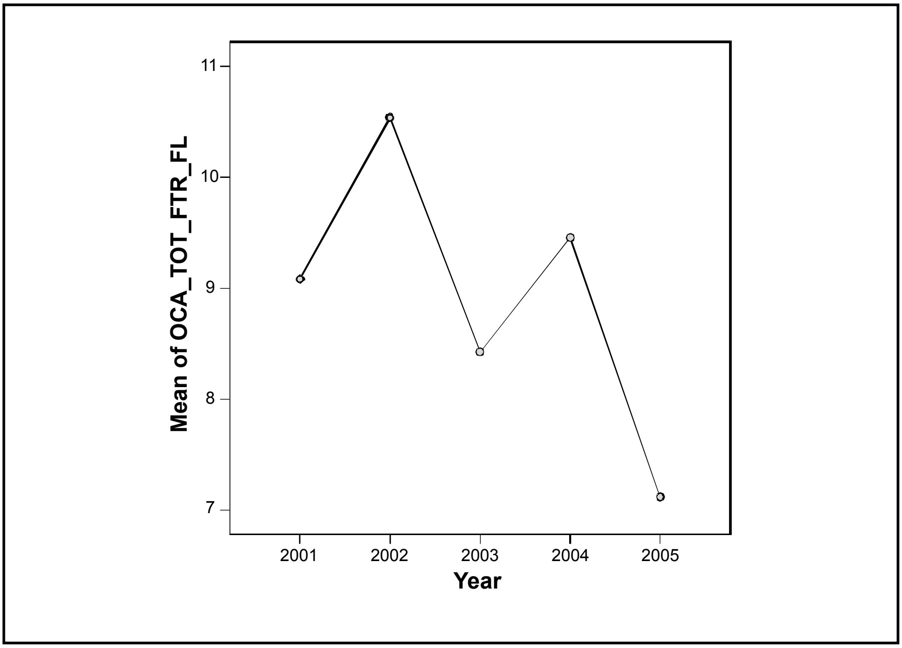
Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 54.405.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots

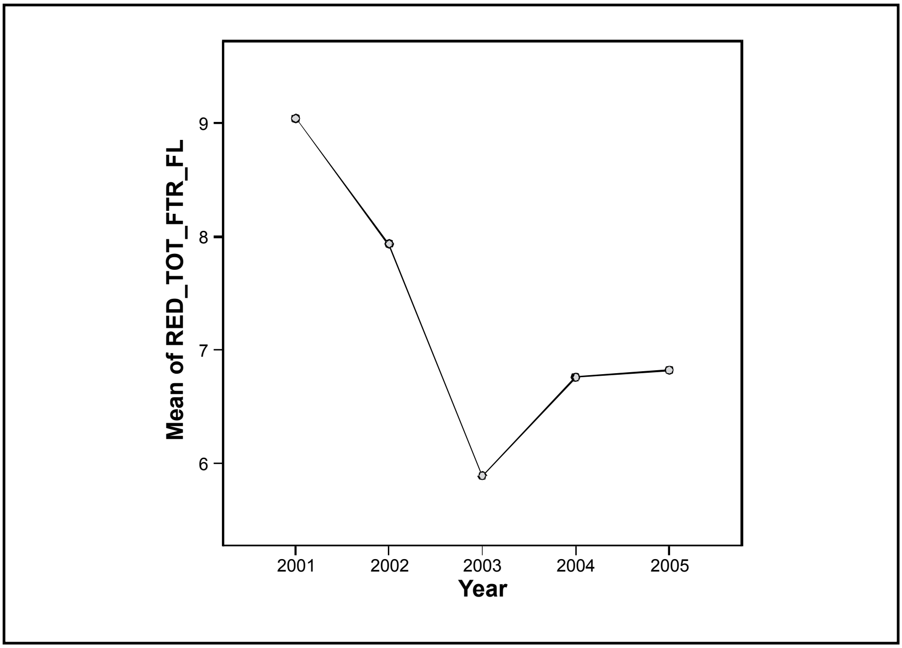



1.8000
1.6000
1.4000
1.2000
1.0000
Mean of FLOWN_RATIO
2001
2002
2003
2004
2005
Year


10.0
9.5
9.0
8.5
8.0
7.5
7.0
Mean of OCA_F15_FL
2001
2002
2003
2004
2005
Year



Mean of OCA_TOT_FTR_FL
11
10
9
8
7
2001
2002
2003
2004
2005
Year



Mean of RED_TOT_FTR_FL
9
8
7
6
2001
2002
2003
2004
2005
Year

A2. 2001 Attrition ANOVA

Author's original work using SPSS 12.0.1

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
F15_ING_ATT	3-1	12	.119048	.1170558	.0337911	.044674	.193421	.0000	.2857
	3-2	15	.194444	.1108081	.0286105	.133081	.255808	.0000	.5000
	3-3	16	.228795	.1785975	.0446494	.133627	.323963	.0000	.6250
	4-1	15	.190079	.1521141	.0392757	.105841	.274317	.0000	.3750
	4-2	14	.135204	.1146017	.0306286	.069035	.201373	.0000	.2500
	Total	72	.177083	.1409508	.0166112	.143962	.210205	.0000	.6250
OCA_ING_ATT	3-1	13	.119505	.1120846	.0310867	.051773	.187238	.0000	.2857
	3-2	15	.194444	.1108081	.0286105	.133081	.255808	.0000	.5000
	3-3	17	.178591	.1435578	.0348179	.104780	.252401	.0000	.5000
	4-1	15	.136263	.1049751	.0271044	.078129	.194396	.0000	.2727
	4-2	14	.135204	.1146017	.0306286	.069035	.201373	.0000	.2500
	Total	74	.154636	.1192056	.0138574	.127018	.182254	.0000	.5000
RED_ING_ATT	3-1	13	.578144	.3011503	.0835241	.396161	.760127	.0000	1.0000
	3-2	15	.406402	.1149174	.0296716	.342763	.470042	.1667	.5833
	3-3	17	.575817	.1964744	.0476520	.474799	.676835	.3333	1.0000
	4-1	15	.629233	.2551380	.0658763	.487942	.770523	.0000	1.0000
	4-2	14	.663690	.1974868	.0527806	.549665	.777716	.3333	1.0000
	Total	74	.569337	.2307686	.0268263	.515873	.622802	.0000	1.0000

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	1.896	4	67	.121
OCA_ING_ATT	.971	4	69	.429
RED_ING_ATT	2.178	4	69	.080

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.115	4	.029	1.484	.217
	Within Groups	1.296	67	.019		
	Total	1.411	71			
OCA_ING_ATT	Between Groups	.060	4	.015	1.058	.384
	Within Groups	.977	69	.014		
	Total	1.037	73			
RED_ING_ATT	Between Groups	.578	4	.145	3.015	.024
	Within Groups	3.309	69	.048		
	Total	3.888	73			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_ING_ATT	3-1	3-2	-.0753968	.0538604	.630	-.226392	.075598
		3-3	-.1097470	.0531071	.247	-.258630	.039136
		4-1	-.0710317	.0538604	.681	-.222027	.079963
		4-2	-.0161565	.0547087	.998	-.169530	.137217
	3-2	3-1	.0753968	.0538604	.630	-.075598	.226392
		3-3	-.0343502	.0499803	.959	-.174468	.105767
		4-1	.0043651	.0507801	1.000	-.137994	.146725
		4-2	.0592404	.0516789	.781	-.085639	.204120
	3-3	3-1	.1097470	.0531071	.247	-.039136	.258630
		3-2	.0343502	.0499803	.959	-.105767	.174468
		4-1	.0387153	.0499803	.937	-.101402	.178833
		4-2	.0935906	.0508933	.360	-.049086	.236267
	4-1	3-1	.0710317	.0538604	.681	-.079963	.222027
		3-2	-.0043651	.0507801	1.000	-.146725	.137994
		3-3	-.0387153	.0499803	.937	-.178833	.101402
		4-2	.0548753	.0516789	.825	-.090004	.199755
	4-2	3-1	.0161565	.0547087	.998	-.137217	.169530
		3-2	-.0592404	.0516789	.781	-.204120	.085639
		3-3	-.0935906	.0508933	.360	-.236267	.049086
		4-1	-.0548753	.0516789	.825	-.199755	.090004
OCA_ING_ATT	3-1	3-2	-.0749389	.0450998	.464	-.201274	.051396
		3-3	-.0590850	.0438508	.663	-.181921	.063751
		4-1	-.0167571	.0450998	.996	-.143092	.109577
		4-2	-.0156986	.0458416	.997	-.144111	.112714
	3-2	3-1	.0749389	.0450998	.464	-.051396	.201274
		3-3	.0158539	.0421617	.996	-.102250	.133958
		4-1	.0581818	.0434593	.668	-.063557	.179921
		4-2	.0592404	.0442286	.668	-.064654	.183134
	3-3	3-1	.0590850	.0438508	.663	-.063751	.181921
		3-2	-.0158539	.0421617	.996	-.133958	.102250
		4-1	.0423279	.0421617	.853	-.075776	.160432
		4-2	.0433864	.0429542	.850	-.076938	.163711

Post-Hoc Tests (continued)

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
RED_ING_ATT	4-1	3-1	.0167571	.0450998	.996	-.109577	.143092
		3-2	-.0581818	.0434593	.668	-.179921	.063557
		3-3	-.0423279	.0421617	.853	-.160432	.075776
		4-2	.0010585	.0442286	1.000	-.122835	.124952
	4-2	3-1	.0156986	.0458416	.997	-.112714	.144111
		3-2	-.0592404	.0442286	.668	-.183134	.064654
		3-3	-.0433864	.0429542	.850	-.163711	.076938
		4-1	-.0010585	.0442286	1.000	-.124952	.122835
	3-1	3-2	.1717416	.0829844	.245	-.060716	.404199
		3-3	.0023271	.0806862	1.000	-.223693	.228347
		4-1	-.0510887	.0829844	.972	-.283546	.181369
		4-2	-.0855464	.0843492	.848	-.321827	.150734
	3-2	3-1	-.1717416	.0829844	.245	-.404199	.060716
		3-3	-.1694145	.0775782	.198	-.386728	.047899
		4-1	-.2228303	.0799658	.052	-.446832	.001171
		4-2	-.2572880(*)	.0813812	.019	-.485255	-.029321
	3-3	3-1	-.0023271	.0806862	1.000	-.228347	.223693
		3-2	.1694145	.0775782	.198	-.047899	.386728
		4-1	-.0534158	.0775782	.958	-.270729	.163898
		4-2	-.0878735	.0790364	.800	-.309272	.133525
	4-1	3-1	.0510887	.0829844	.972	-.181369	.283546
		3-2	.2228303	.0799658	.052	-.001171	.446832
		3-3	.0534158	.0775782	.958	-.163898	.270729
		4-2	-.0344577	.0813812	.993	-.262424	.193509
	4-2	3-1	.0855464	.0843492	.848	-.150734	.321827
		3-2	.2572880(*)	.0813812	.019	.029321	.485255
		3-3	.0878735	.0790364	.800	-.133525	.309272
		4-1	.0344577	.0813812	.993	-.193509	.262424

* The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_ING_ATT

Tukey HSD

F1	N	Subset for alpha = .05
		1
3-1	12	.119048
4-2	14	.135204
4-1	15	.190079
3-2	15	.194444
3-3	16	.228795
Sig.		.229

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.261.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_ING_ATT

Tukey HSD

F1	N	Subset for alpha = .05
		1
3-1	13	.119505
4-2	14	.135204
4-1	15	.136263
3-3	17	.178591
3-2	15	.194444
Sig.		.437

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

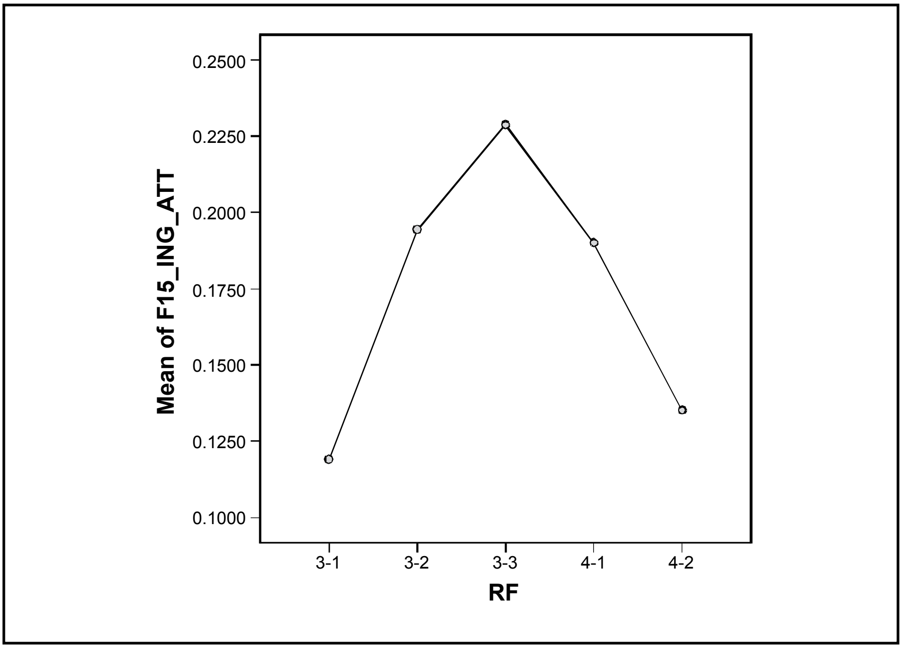
RED_ING_ATT

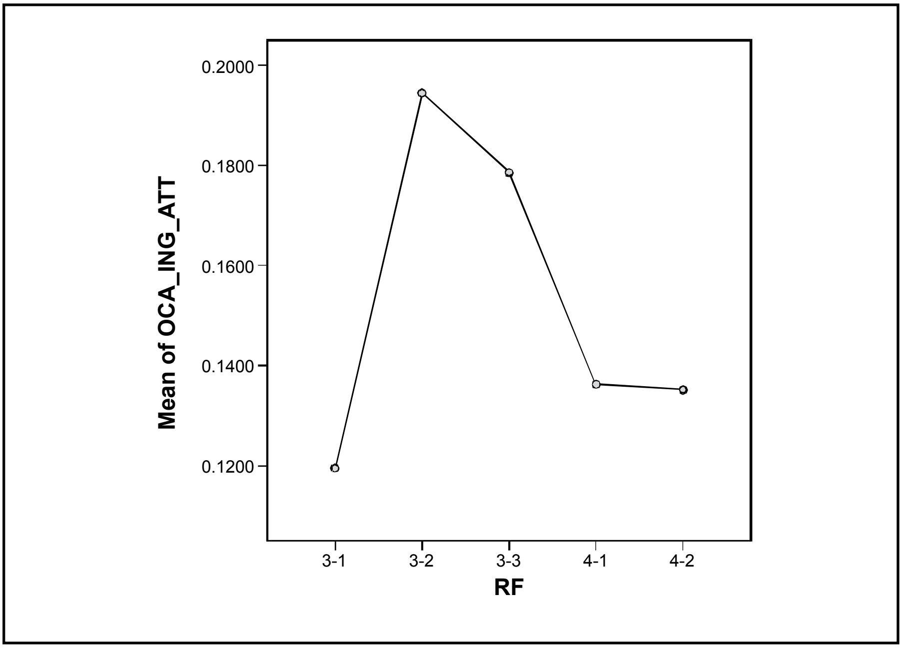
Tukey HSD

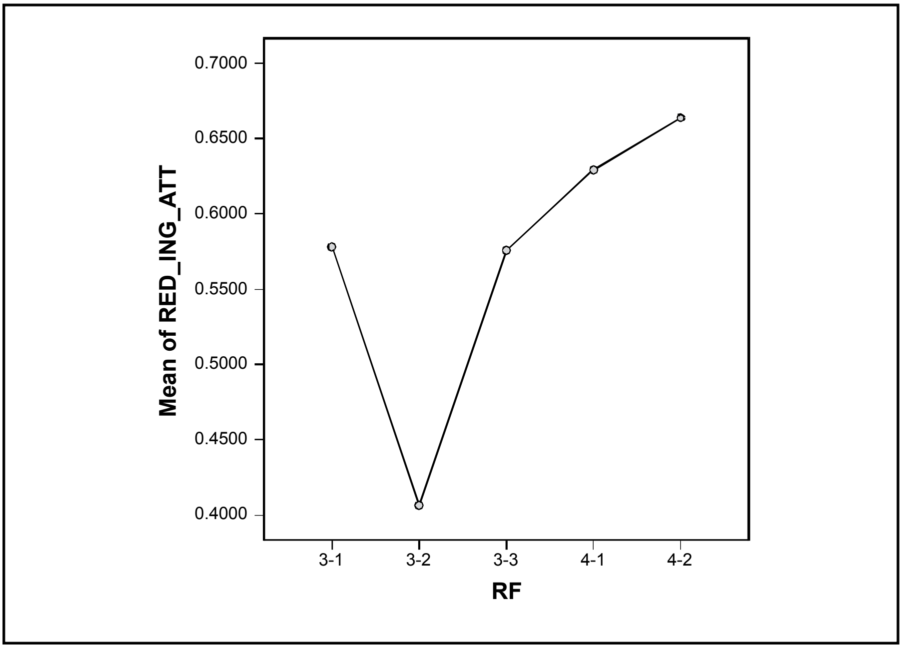
F1	N	Subset for alpha = .05	
		1	2
3-2	15	.406402	
3-3	17	.575817	.575817
3-1	13	.578144	.578144
4-1	15	.629233	.629233
4-2	14		.663690
Sig.		.056	.812

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots




Mean of OCA_ING_ATT
0.2000
0.1800
0.1600
0.1400
0.1200
3-1
3-2
3-3
4-1
4-2
RF


Mean of RED_ING_ATT
0.7000
0.6500
0.6000
0.5500
0.5000
0.4500
0.4000
3-1
3-2
3-3
4-1
4-2
RF

2001 Force Ratio ANOVA

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Mini-mum	Maxi-mum
						Lower Bound	Upper Bound		
F15_FLOWN_RATIO	3-1	13	.881716	.2762661	.0766224	.714770	1.048661	.0000	1.1429
	3-2	15	.729868	.1320880	.0341050	.656720	.803016	.5000	.9091
	3-3	17	.866667	.3190456	.0773799	.702629	1.030705	.0000	1.6000
	4-1	15	.896296	.0887565	.0229168	.847145	.945448	.6667	1.0000
	4-2	14	.880952	.0684142	.0182845	.841451	.920454	.7778	1.0000
	Total	74	.850290	.2106658	.0244894	.801482	.899097	.0000	1.6000
FLOWN_RATIO	3-1	13	.950092	.0804809	.0223214	.901457	.998726	.8750	1.1429
	3-2	15	.729868	.1320880	.0341050	.656720	.803016	.5000	.9091
	3-3	17	1.283497	.4437793	.1076323	1.055326	1.511667	.4444	2.4000
	4-1	15	1.321429	.1222615	.0315678	1.253722	1.389135	1.1111	1.5714
	4-2	14	.880952	.0684142	.0182845	.841451	.920454	.7778	1.0000
	Total	74	1.044235	.3277100	.0380955	.968311	1.120160	.4444	2.4000

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_FLOWN_RATIO	2.199	4	69	.078
FLOWN_RATIO	6.293	4	69	.000

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
F15_FLOWN_RATIO	Between Groups	.280	4	.070	1.631	.176
	Within Groups	2.960	69	.043		
	Total	3.240	73			
FLOWN_RATIO	Between Groups	4.097	4	1.024	18.879	.000
	Within Groups	3.743	69	.054		
	Total	7.840	73			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_FLOWN_RATIO	3-1	3-2	.1518476	.0784832	.309	-.068001	.371696
		3-3	.0150488	.0763097	1.000	-.198711	.228809
		4-1	-.0145808	.0784832	1.000	-.234430	.205268
		4-2	.0007631	.0797740	1.000	-.222701	.224228
	3-2	3-1	-.1518476	.0784832	.309	-.371696	.068001
		3-3	-.1367988	.0733702	.346	-.342325	.068727
		4-1	-.1664284	.0756283	.192	-.378280	.045423
		4-2	-.1510845	.0769670	.295	-.366686	.064517
	3-3	3-1	-.0150488	.0763097	1.000	-.228809	.198711
		3-2	.1367988	.0733702	.346	-.068727	.342325
		4-1	-.0296296	.0733702	.994	-.235156	.175897
		4-2	-.0142857	.0747493	1.000	-.223675	.195104
	4-1	3-1	.0145808	.0784832	1.000	-.205268	.234430
		3-2	.1664284	.0756283	.192	-.045423	.378280
		3-3	.0296296	.0733702	.994	-.175897	.235156
		4-2	.0153439	.0769670	1.000	-.200257	.230945
	4-2	3-1	-.0007631	.0797740	1.000	-.224228	.222701
		3-2	.1510845	.0769670	.295	-.064517	.366686
		3-3	.0142857	.0747493	1.000	-.195104	.223675
		4-1	-.0153439	.0769670	1.000	-.230945	.200257
FLOWN_RATIO	3-1	3-2	.2202237	.0882583	.104	-.027007	.467455
		3-3	-.3334052(*)	.0858140	.002	-.573789	-.093021
		4-1	-.3713370(*)	.0882583	.001	-.618568	-.124106
		4-2	.0691392	.0897098	.938	-.182158	.320436
	3-2	3-1	-.2202237	.0882583	.104	-.467455	.027007
		3-3	-.5536288(*)	.0825085	.000	-.784753	-.322504
		4-1	-.5915607(*)	.0850478	.000	-.829798	-.353323
		4-2	-.1510845	.0865532	.414	-.393539	.091370
	3-3	3-1	.3334052(*)	.0858140	.002	.093021	.573789
		3-2	.5536288(*)	.0825085	.000	.322504	.784753
		4-1	-.0379318	.0825085	.991	-.269056	.193193
		4-2	.4025444(*)	.0840594	.000	.167076	.638013

Post-Hoc Tests (continued)

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	4-1	3-1	.3713370(*)	.0882583	.001	.124106	.618568
		3-2	.5915607(*)	.0850478	.000	.353323	.829798
		3-3	.0379318	.0825085	.991	-.193193	.269056
		4-2	.4404762(*)	.0865532	.000	.198022	.682931
	4-2	3-1	-.0691392	.0897098	.938	-.320436	.182158
		3-2	.1510845	.0865532	.414	-.091370	.393539
		3-3	-.4025444(*)	.0840594	.000	-.638013	-.167076
		4-1	-.4404762(*)	.0865532	.000	-.682931	-.198022

* The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_FLOWN_RATIO

Tukey HSD

F1	N	Subset for alpha = .05
		1
3-2	15	.729868
3-3	17	.866667
4-2	14	.880952
3-1	13	.881716
4-1	15	.896296
Sig.		.201

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

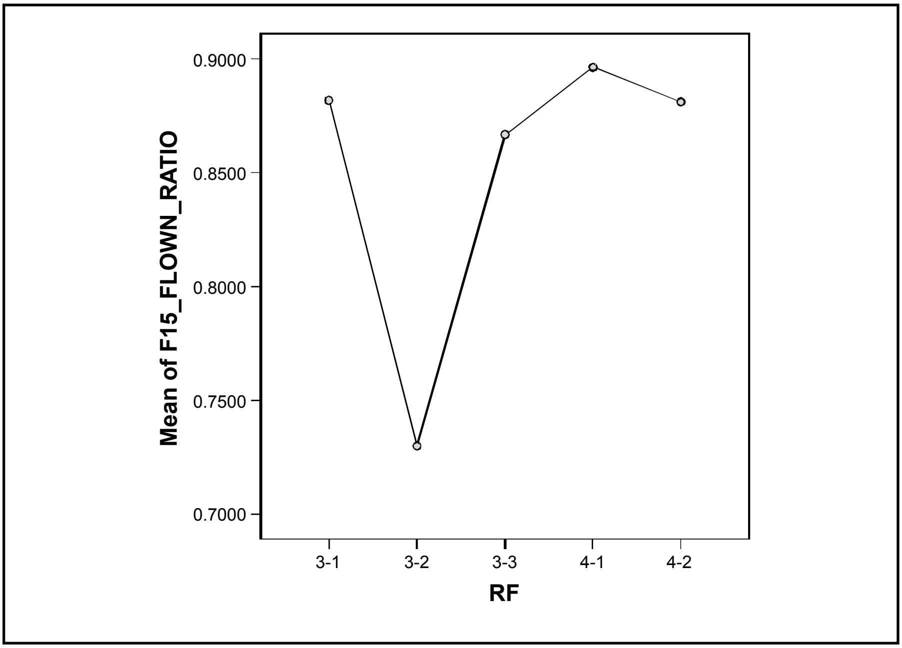
FLOWN_RATIO

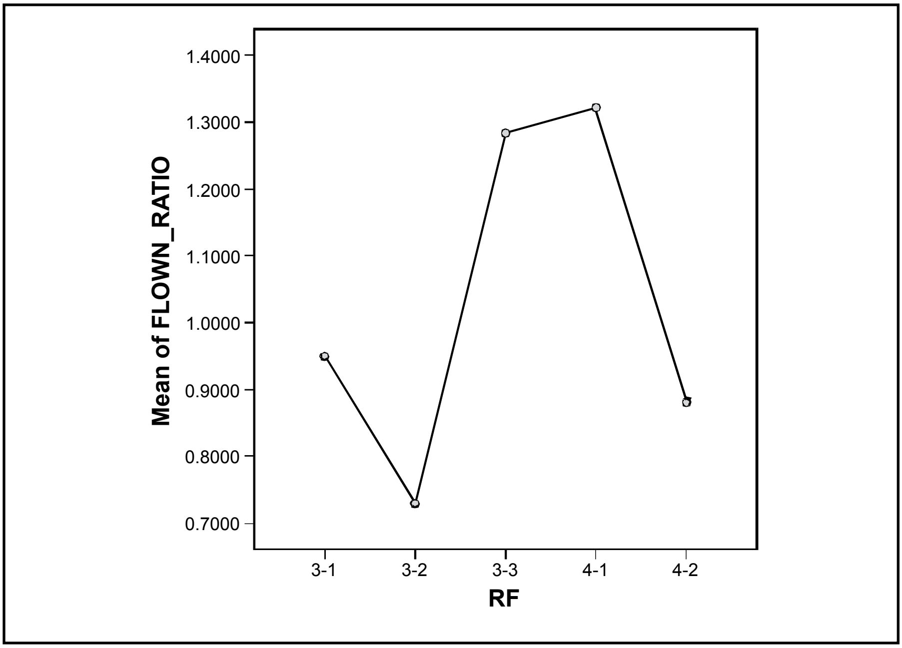
Tukey HSD

F1	N	Subset for alpha = .05	
		1	2
3-2	15	.729868	
4-2	14	.880952	
3-1	13	.950092	
3-3	17		1.283497
4-1	15		1.321429
Sig.		.089	.992

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots




Mean of FLOWN_RATIO
1.4000
1.3000
1.2000
1.1000
1.0000
0.9000
0.8000
0.7000
3-1
3-2
3-3
4-1
4-2
RF

2001 Force Ratio and Aircraft Sortie ANOVA

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
F15_FLOWN_RATIO	3-1	13	.881716	.2762661	.0766224	.714770	1.048661	.0000	1.1429
	3-2	15	.729868	.1320880	.0341050	.656720	.803016	.5000	.9091
	3-3	17	.866667	.3190456	.0773799	.702629	1.030705	.0000	1.6000
	4-1	15	.896296	.0887565	.0229168	.847145	.945448	.6667	1.0000
	4-2	14	.880952	.0684142	.0182845	.841451	.920454	.7778	1.0000
	Total	74	.850290	.2106658	.0244894	.801482	.899097	.0000	1.6000
FLOWN_RATIO	3-1	13	.950092	.0804809	.0223214	.901457	.998726	.8750	1.1429
	3-2	15	.729868	.1320880	.0341050	.656720	.803016	.5000	.9091
	3-3	17	1.283497	.4437793	.1076323	1.055326	1.511667	.4444	2.4000
	4-1	15	1.321429	.1222615	.0315678	1.253722	1.389135	1.1111	1.5714
	4-2	14	.880952	.0684142	.0182845	.841451	.920454	.7778	1.0000
	Total	74	1.044235	.3277100	.0380955	.968311	1.120160	.4444	2.4000
OCA_F15_FL	3-1	12	7.58	.669	.193	7.16	8.01	6	8
	3-2	15	8.53	1.767	.456	7.55	9.51	4	10
	3-3	16	7.06	1.611	.403	6.20	7.92	4	8
	4-1	15	7.73	.594	.153	7.40	8.06	6	8
	4-2	14	7.79	.426	.114	7.54	8.03	7	8
	Total	72	7.74	1.256	.148	7.44	8.03	4	10
OCA_TOT_FTR_FL	3-1	13	7.62	.650	.180	7.22	8.01	6	8
	3-2	15	8.53	1.767	.456	7.55	9.51	4	10
	3-3	17	9.71	2.568	.623	8.39	11.03	4	12
	4-1	15	11.40	.737	.190	10.99	11.81	10	12
	4-2	14	7.79	.426	.114	7.54	8.03	7	8
	Total	74	9.08	2.052	.239	8.61	9.56	4	12
RED_TOT_FTR_FL	3-1	13	8.08	1.038	.288	7.45	8.70	6	9
	3-2	15	11.67	1.345	.347	10.92	12.41	8	13
	3-3	17	7.94	1.638	.397	7.10	8.78	4	9
	4-1	15	8.67	.617	.159	8.32	9.01	7	9
	4-2	14	8.86	.363	.097	8.65	9.07	8	9
	Total	74	9.04	1.763	.205	8.63	9.45	4	13

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_FLOWN_RATIO	2.199	4	69	.078
FLOWN_RATIO	6.293	4	69	.000
OCA_F15_FL	7.536	4	67	.000
OCA_TOT_FTR_FL	12.991	4	69	.000
RED_TOT_FTR_FL	3.835	4	69	.007

ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
F15_FLOWN_RATIO	Between Groups	.280	4	.070	1.631	.176
	Within Groups	2.960	69	.043		
	Total	3.240	73			
FLOWN_RATIO	Between Groups	4.097	4	1.024	18.879	.000
	Within Groups	3.743	69	.054		
	Total	7.840	73			
OCA_F15_FL	Between Groups	17.108	4	4.277	3.020	.024
	Within Groups	94.878	67	1.416		
	Total	111.986	71			
OCA_TOT_FTR_FL	Between Groups	143.217	4	35.804	15.037	.000
	Within Groups	164.297	69	2.381		
	Total	307.514	73			
RED_TOT_FTR_FL	Between Groups	138.633	4	34.658	27.100	.000
	Within Groups	88.245	69	1.279		
	Total	226.878	73			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_FLOWN_RATIO	3-1	3-2	.1518476	.0784832	.309	-.068001	.371696
		3-3	.0150488	.0763097	1.000	-.198711	.228809
		4-1	-.0145808	.0784832	1.000	-.234430	.205268
		4-2	.0007631	.0797740	1.000	-.222701	.224228
	3-2	3-1	-.1518476	.0784832	.309	-.371696	.068001
		3-3	-.1367988	.0733702	.346	-.342325	.068727
		4-1	-.1664284	.0756283	.192	-.378280	.045423
		4-2	-.1510845	.0769670	.295	-.366686	.064517
	3-3	3-1	-.0150488	.0763097	1.000	-.228809	.198711
		3-2	.1367988	.0733702	.346	-.068727	.342325
		4-1	-.0296296	.0733702	.994	-.235156	.175897
		4-2	-.0142857	.0747493	1.000	-.223675	.195104
	4-1	3-1	.0145808	.0784832	1.000	-.205268	.234430
		3-2	.1664284	.0756283	.192	-.045423	.378280
		3-3	.0296296	.0733702	.994	-.175897	.235156
		4-2	.0153439	.0769670	1.000	-.200257	.230945
	4-2	3-1	-.0007631	.0797740	1.000	-.224228	.222701
		3-2	.1510845	.0769670	.295	-.064517	.366686
		3-3	.0142857	.0747493	1.000	-.195104	.223675
		4-1	-.0153439	.0769670	1.000	-.230945	.200257
FLOWN_RATIO	3-1	3-2	.2202237	.0882583	.104	-.027007	.467455
		3-3	-.3334052(*)	.0858140	.002	-.573789	-.093021
		4-1	-.3713370(*)	.0882583	.001	-.618568	-.124106
		4-2	.0691392	.0897098	.938	-.182158	.320436
	3-2	3-1	-.2202237	.0882583	.104	-.467455	.027007
		3-3	-.5536288(*)	.0825085	.000	-.784753	-.322504
		4-1	-.5915607(*)	.0850478	.000	-.829798	-.353323
		4-2	-.1510845	.0865532	.414	-.393539	.091370
	3-3	3-1	.3334052(*)	.0858140	.002	.093021	.573789
		3-2	.5536288(*)	.0825085	.000	.322504	.784753
		4-1	-.0379318	.0825085	.991	-.269056	.193193
		4-2	.4025444(*)	.0840594	.000	.167076	.638013

Post-Hoc Tests (continued)

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	4-1	3-1	.3713370(*)	.0882583	.001	.124106	.618568
		3-2	.5915607(*)	.0850478	.000	.353323	.829798
		3-3	.0379318	.0825085	.991	-.193193	.269056
		4-2	.4404762(*)	.0865532	.000	.198022	.682931
	4-2	3-1	-.0691392	.0897098	.938	-.320436	.182158
		3-2	.1510845	.0865532	.414	-.091370	.393539
		3-3	-.4025444(*)	.0840594	.000	-.638013	-.167076
		4-1	-.4404762(*)	.0865532	.000	-.682931	-.198022
OCA_F15_FL	3-1	3-2	-.950	.461	.249	-2.24	.34
		3-3	.521	.454	.781	-.75	1.79
		4-1	-.150	.461	.998	-1.44	1.14
		4-2	-.202	.468	.993	-1.51	1.11
	3-2	3-1	.950	.461	.249	-.34	2.24
		3-3	1.471(*)	.428	.009	.27	2.67
		4-1	.800	.435	.359	-.42	2.02
		4-2	.748	.442	.447	-.49	1.99
	3-3	3-1	-.521	.454	.781	-1.79	.75
		3-2	-1.471(*)	.428	.009	-2.67	-.27
		4-1	-.671	.428	.523	-1.87	.53
		4-2	-.723	.435	.465	-1.94	.50
	4-1	3-1	.150	.461	.998	-1.14	1.44
		3-2	-.800	.435	.359	-2.02	.42
		3-3	.671	.428	.523	-.53	1.87
		4-2	-.052	.442	1.000	-1.29	1.19
	4-2	3-1	.202	.468	.993	-1.11	1.51
		3-2	-.748	.442	.447	-1.99	.49
		3-3	.723	.435	.465	-.50	1.94
		4-1	.052	.442	1.000	-1.19	1.29
OCA_TOT_FTR_FL	3-1	3-2	-.918	.585	.522	-2.56	.72
		3-3	-2.090(*)	.569	.004	-3.68	-.50
		4-1	-3.785(*)	.585	.000	-5.42	-2.15
		4-2	-.170	.594	.998	-1.84	1.49
	3-2	3-1	.918	.585	.522	-.72	2.56
		3-3	-1.173	.547	.213	-2.70	.36

Post-Hoc Tests (continued)

Dependent Variable	(I) F1	(J) F1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
		4-1	-2.867(*)	.563	.000	-4.45	-1.29
		4-2	.748	.573	.690	-.86	2.35
	3-3	3-1	2.090(*)	.569	.004	.50	3.68
		3-2	1.173	.547	.213	-.36	2.70
		4-1	-1.694(*)	.547	.023	-3.23	-.16
		4-2	1.920(*)	.557	.008	.36	3.48
	4-1	3-1	3.785(*)	.585	.000	2.15	5.42
		3-2	2.867(*)	.563	.000	1.29	4.45
		3-3	1.694(*)	.547	.023	.16	3.23
		4-2	3.614(*)	.573	.000	2.01	5.22
	4-2	3-1	.170	.594	.998	-1.49	1.84
		3-2	-.748	.573	.690	-2.35	.86
		3-3	-1.920(*)	.557	.008	-3.48	-.36
		4-1	-3.614(*)	.573	.000	-5.22	-2.01
RED_TOT_FTR_FL	3-1	3-2	-3.590(*)	.429	.000	-4.79	-2.39
		3-3	.136	.417	.998	-1.03	1.30
		4-1	-.590	.429	.645	-1.79	.61
		4-2	-.780	.436	.387	-2.00	.44
	3-2	3-1	3.590(*)	.429	.000	2.39	4.79
		3-3	3.725(*)	.401	.000	2.60	4.85
		4-1	3.000(*)	.413	.000	1.84	4.16
		4-2	2.810(*)	.420	.000	1.63	3.99
	3-3	3-1	-.136	.417	.998	-1.30	1.03
		3-2	-3.725(*)	.401	.000	-4.85	-2.60
		4-1	-.725	.401	.376	-1.85	.40
		4-2	-.916	.408	.176	-2.06	.23
	4-1	3-1	.590	.429	.645	-.61	1.79
		3-2	-3.000(*)	.413	.000	-4.16	-1.84
		3-3	.725	.401	.376	-.40	1.85
		4-2	-.190	.420	.991	-1.37	.99
	4-2	3-1	.780	.436	.387	-.44	2.00
		3-2	-2.810(*)	.420	.000	-3.99	-1.63
		3-3	.916	.408	.176	-.23	2.06
		4-1	.190	.420	.991	-.99	1.37

* The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_FLOWN_RATIO

Tukey HSD

F1	N	Subset for alpha = .05
		1
3-2	15	.729868
3-3	17	.866667
4-2	14	.880952
3-1	13	.881716
4-1	15	.896296
Sig.		.201

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

FLOWN_RATIO

Tukey HSD

F1	N	Subset for alpha = .05	
		1	2
3-2	15	.729868	
4-2	14	.880952	
3-1	13	.950092	
3-3	17		1.283497
4-1	15		1.321429
Sig.		.089	.992

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_F15_FL

Tukey HSD

F1	N	Subset for alpha = .05	
		1	2
3-3	16	7.06	
3-1	12	7.58	7.58
4-1	15	7.73	7.73
4-2	14	7.79	7.79
3-2	15		8.53
Sig.		.488	.219

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.261.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_TOT_FTR_FL

Tukey HSD

F1	N	Subset for alpha = .05		
		1	2	3
3-1	13	7.62		
4-2	14	7.79		
3-2	15	8.53	8.53	
3-3	17		9.71	
4-1	15			11.40
Sig.		.495	.250	1.000

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

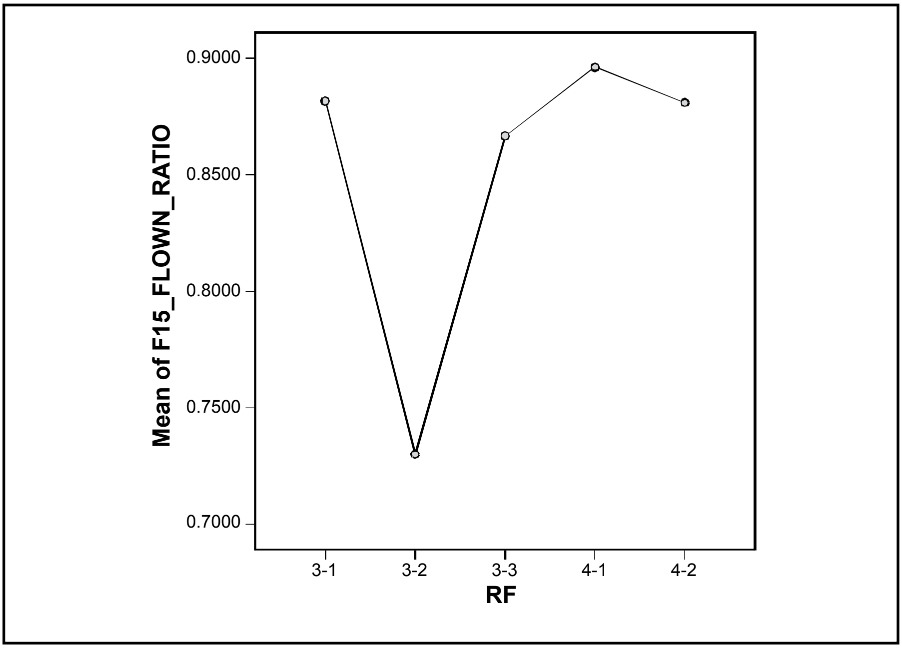
RED_TOT_FTR_FL

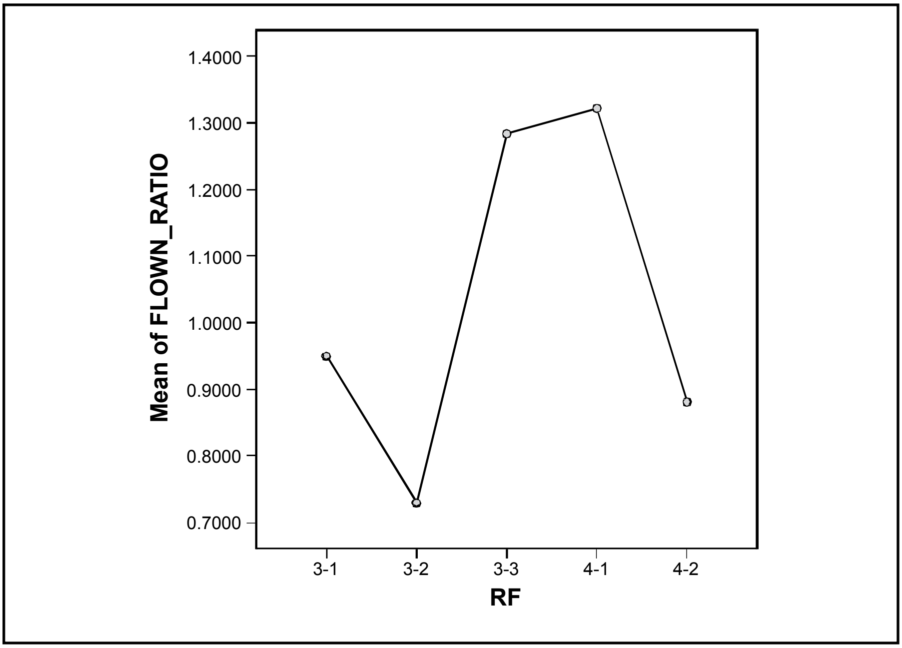
Tukey HSD

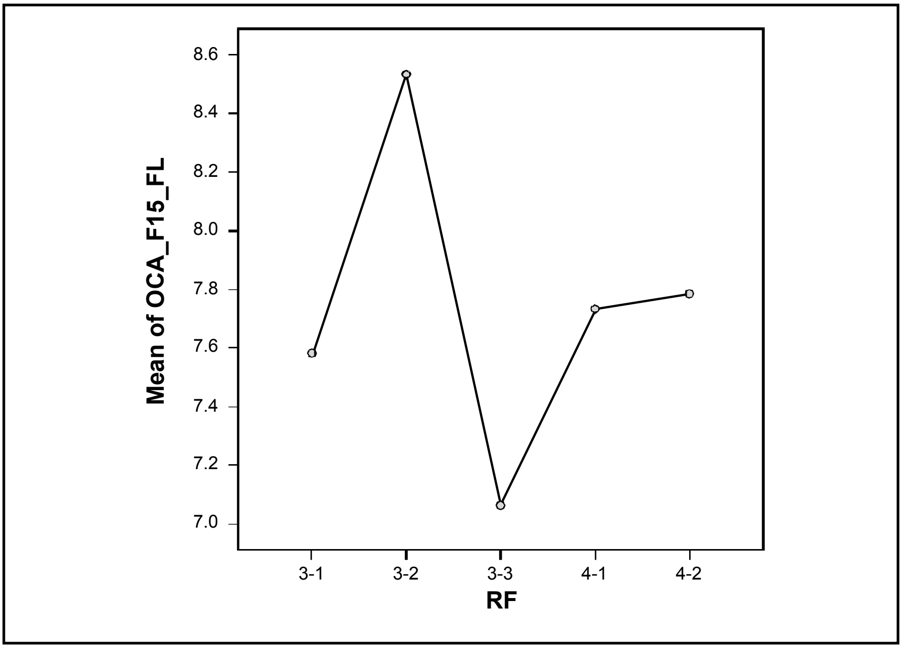
F1	N	Subset for alpha = .05	
		1	2
3-3	17	7.94	
3-1	13	8.08	
4-1	15	8.67	
4-2	14	8.86	
3-2	15		11.67
Sig.		.194	1.000

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 14.684.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots




Mean of FLOWN_RATIO
1.4000
1.3000
1.2000
1.1000
1.0000
0.9000
0.8000
0.7000
3-1
3-2
3-3
4-1
4-2
RF


Mean of OCA_F15_FL
8.6
8.4
8.2
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7.6
7.4
7.2
7.0
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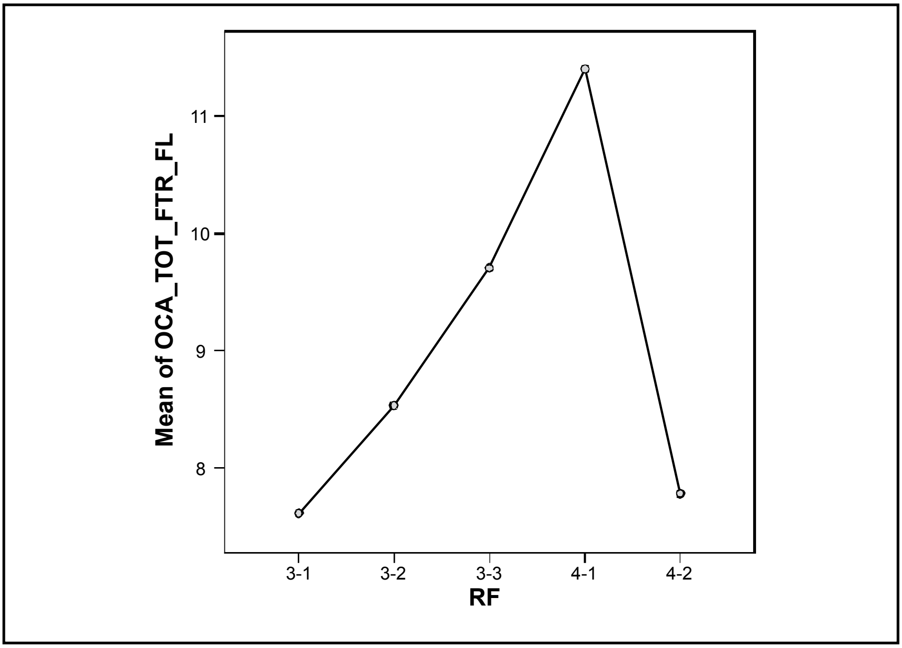
3-2
3-3
4-1
4-2
RF


Mean of OCA_TOT_FTR_FL
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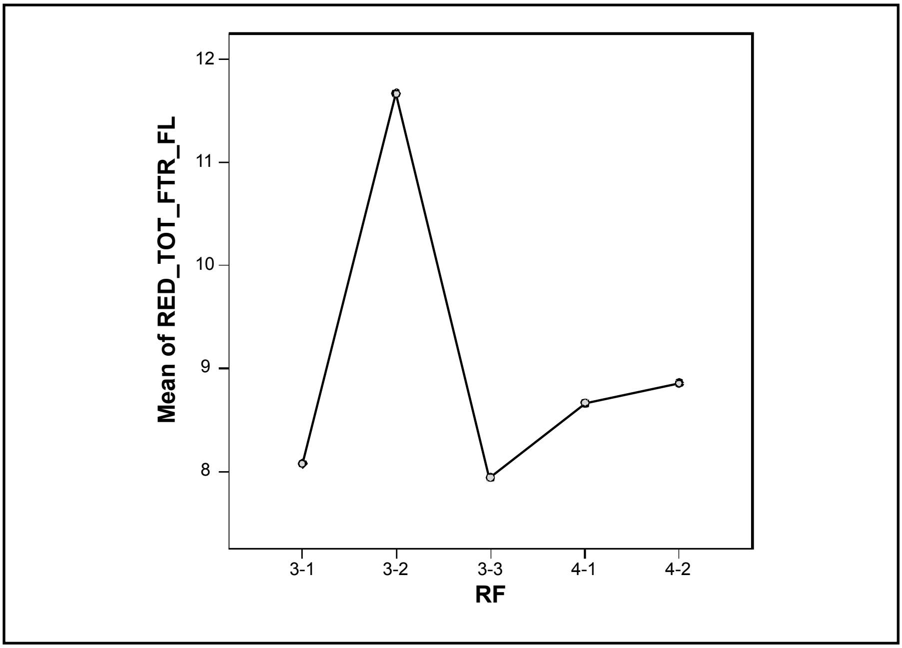
10
9
8
3-1
3-2
3-3
4-1
4-2
RF


Mean of RED_TOT_FTR_FL
12
11
10
9
8
3-1
3-2
3-3
4-1
4-2
RF

A3. Variation in Attrition by Week and Day T-Test

Author's original work using SPSS 12.0.1

Group Statistics

	WK	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	1	140	.122828	.1533635	.0129616
	2	159	.139354	.1519543	.0120508
OCA_ING_ATT	1	140	.113246	.1414239	.0119525
	2	167	.131077	.1386506	.0107291
RED_ING_ATT	1	140	.698957	.2210454	.0186817
	2	167	.733215	.2253592	.0174388

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	.059	.809	-.934	297	.351	-.0165254	.0176877	-.0513345	.0182837
	Equal variances not assumed			-.934	291.529	.351	-.0165254	.0176981	-.0513577	.0183069
OCA_ING_ATT	Equal variances assumed	.169	.681	-1.112	305	.267	-.0178308	.0160336	-.0493812	.0137197
	Equal variances not assumed			-1.110	293.621	.268	-.0178308	.0160616	-.0494413	.0137797
RED_ING_ATT	Equal variances assumed	.331	.565	-1.338	305	.182	-.0342581	.0255998	-.0846328	.0161165
	Equal variances not assumed			-1.341	297.582	.181	-.0342581	.0255562	-.0845519	.0160357

WEEK 1: Monday–Friday ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.026	4	.006	.266	.899
	Within Groups	3.244	135	.024		
	Total	3.269	139			
OCA_ING_ATT	Between Groups	.017	4	.004	.213	.931
	Within Groups	2.763	135	.020		
	Total	2.780	139			
RED_ING_ATT	Between Groups	.223	4	.056	1.145	.338
	Within Groups	6.569	135	.049		
	Total	6.792	139			

WEEK 2: Monday–Friday ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.278	4	.069	3.175	.015
	Within Groups	3.370	154	.022		
	Total	3.648	158			
OCA_ING_ATT	Between Groups	.278	4	.069	3.863	.005
	Within Groups	2.913	162	.018		
	Total	3.191	166			
RED_ING_ATT	Between Groups	.202	4	.051	.994	.412
	Within Groups	8.229	162	.051		
	Total	8.431	166			

WEEK 2: Monday–Friday ANOVA

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
F15_ING_ATT	MON	37	.091763	.1170542	.0192436	.052735	.130791	.0000	.3750
	TUE	37	.104794	.1051496	.0172865	.069735	.139853	.0000	.3750
	WED	35	.149107	.1618597	.0273593	.093506	.204708	.0000	.7500
	THU	34	.190278	.1720798	.0295114	.130236	.250319	.0000	.6250
	FRI	16	.199777	.2018430	.0504607	.092222	.307331	.0000	.5714
	Total	159	.139354	.1519543	.0120508	.115552	.163155	.0000	.7500
OCA_ING_ATT	MON	38	.085617	.1045232	.0169559	.051262	.119973	.0000	.2727
	TUE	37	.096101	.0878778	.0144470	.066801	.125401	.0000	.2727
	WED	36	.141738	.1501752	.0250292	.090926	.192550	.0000	.7500
	THU	36	.162207	.1483514	.0247252	.112012	.212402	.0000	.5000
	FRI	20	.206932	.1879903	.0420359	.118950	.294914	.0000	.5000
	Total	167	.131077	.1386506	.0107291	.109894	.152260	.0000	.7500
RED_ING_ATT	MON	38	.773405	.2335313	.0378838	.696646	.850165	.0000	1.0000
	TUE	37	.724625	.2155671	.0354390	.652751	.796498	.2857	1.0000
	WED	36	.726546	.2080172	.0346695	.656163	.796929	.2727	1.0000
	THU	36	.681468	.2435892	.0405982	.599050	.763887	.1111	1.0000
	FRI	20	.777895	.2232032	.0499098	.673433	.882357	.2500	1.0000
	Total	167	.733215	.2253592	.0174388	.698785	.767646	.0000	1.0000

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	3.300	4	154	.013
OCA_ING_ATT	4.818	4	162	.001
RED_ING_ATT	.349	4	162	.844

ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.278	4	.069	3.175	.015
	Within Groups	3.370	154	.022		
	Total	3.648	158			
OCA_ING_ATT	Between Groups	.278	4	.069	3.863	.005
	Within Groups	2.913	162	.018		
	Total	3.191	166			
RED_ING_ATT	Between Groups	.202	4	.051	.994	.412
	Within Groups	8.229	162	.051		
	Total	8.431	166			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) DAY2	(J) DAY2	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_ING_ATT	MON	TUE	-.0130309	.0343946	.996	-.107973	.081911
		WED	-.0573437	.0348825	.472	-.153632	.038945
		THU	-.0985146(*)	.0351451	.045	-.195528	-.001501
		FRI	-.1080136	.0442642	.110	-.230199	.014172
	TUE	MON	.0130309	.0343946	.996	-.081911	.107973
		WED	-.0443128	.0348825	.710	-.140601	.051976
		THU	-.0854837	.0351451	.112	-.182497	.011530
		FRI	-.0949827	.0442642	.206	-.217168	.027203
	WED	MON	.0573437	.0348825	.472	-.038945	.153632
		TUE	.0443128	.0348825	.710	-.051976	.140601
		THU	-.0411709	.0356227	.776	-.139503	.057161
		FRI	-.0506699	.0446444	.788	-.173905	.072565
	THU	MON	.0985146(*)	.0351451	.045	.001501	.195528
		TUE	.0854837	.0351451	.112	-.011530	.182497
		WED	.0411709	.0356227	.776	-.057161	.139503
		FRI	-.0094990	.0448499	1.000	-.133301	.114303
	FRI	MON	.1080136	.0442642	.110	-.014172	.230199
		TUE	.0949827	.0442642	.206	-.027203	.217168
		WED	.0506699	.0446444	.788	-.072565	.173905
		THU	.0094990	.0448499	1.000	-.114303	.133301
OCA_ING_ATT	MON	TUE	-.0104835	.0309724	.997	-.095929	.074962
		WED	-.0561209	.0311896	.378	-.142165	.029923
		THU	-.0765899	.0311896	.106	-.162634	.009454
		FRI	-.1213144(*)	.0370463	.011	-.223516	-.019113
	TUE	MON	.0104835	.0309724	.997	-.074962	.095929
		WED	-.0456374	.0313940	.594	-.132245	.040971
		THU	-.0661064	.0313940	.223	-.152714	.020502
		FRI	-.1108308(*)	.0372185	.027	-.213507	-.008154
	WED	MON	.0561209	.0311896	.378	-.029923	.142165
		TUE	.0456374	.0313940	.594	-.040971	.132245

Post-Hoc Tests (continued)

Dependent Variable	(I) DAY2	(J) DAY2	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
		THU	-.0204690	.0316083	.967	-.107668	.066730
		FRI	-.0651935	.0373994	.411	-.168369	.037982
	THU	MON	.0765899	.0311896	.106	-.009454	.162634
		TUE	.0661064	.0313940	.223	-.020502	.152714
		WED	.0204690	.0316083	.967	-.066730	.107668
		FRI	-.0447244	.0373994	.754	-.147900	.058451
	FRI	MON	.1213144(*)	.0370463	.011	.019113	.223516
		TUE	.1108308(*)	.0372185	.027	.008154	.213507
		WED	.0651935	.0373994	.411	-.037982	.168369
		THU	.0447244	.0373994	.754	-.058451	.147900
RED_ING_ATT	MON	TUE	.0487808	.0520526	.882	-.094819	.192381
		WED	.0468593	.0524176	.899	-.097748	.191466
		THU	.0919370	.0524176	.404	-.052670	.236544
		FRI	-.0044896	.0622604	1.000	-.176250	.167271
	TUE	MON	-.0487808	.0520526	.882	-.192381	.094819
		WED	-.0019216	.0527611	1.000	-.147476	.143633
		THU	.0431562	.0527611	.925	-.102398	.188711
		FRI	-.0532704	.0625498	.914	-.225829	.119289
	WED	MON	-.0468593	.0524176	.899	-.191466	.097748
		TUE	.0019216	.0527611	1.000	-.143633	.147476
		THU	.0450778	.0531213	.915	-.101470	.191626
		FRI	-.0513488	.0628539	.925	-.224747	.122049
	THU	MON	-.0919370	.0524176	.404	-.236544	.052670
		TUE	-.0431562	.0527611	.925	-.188711	.102398
		WED	-.0450778	.0531213	.915	-.191626	.101470
		FRI	-.0964266	.0628539	.542	-.269825	.076971
	FRI	MON	.0044896	.0622604	1.000	-.167271	.176250
		TUE	.0532704	.0625498	.914	-.119289	.225829
		WED	.0513488	.0628539	.925	-.122049	.224747
		THU	.0964266	.0628539	.542	-.076971	.269825

* The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_ING_ATT

Tukey HSD

DAY2	N	Subset for alpha = .05	
		1	2
MON	37	.091763	
TUE	37	.104794	.104794
WED	35	.149107	.149107
THU	34	.190278	.190278
FRI	16		.199777
Sig.		.091	.113

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 28.647.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_ING_ATT

Tukey HSD

DAY2	N	Subset for alpha = .05	
		1	2
MON	38	.085617	
TUE	37	.096101	
WED	36	.141738	.141738
THU	36	.162207	.162207
FRI	20		.206932
Sig.		.162	.307

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 31.467.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

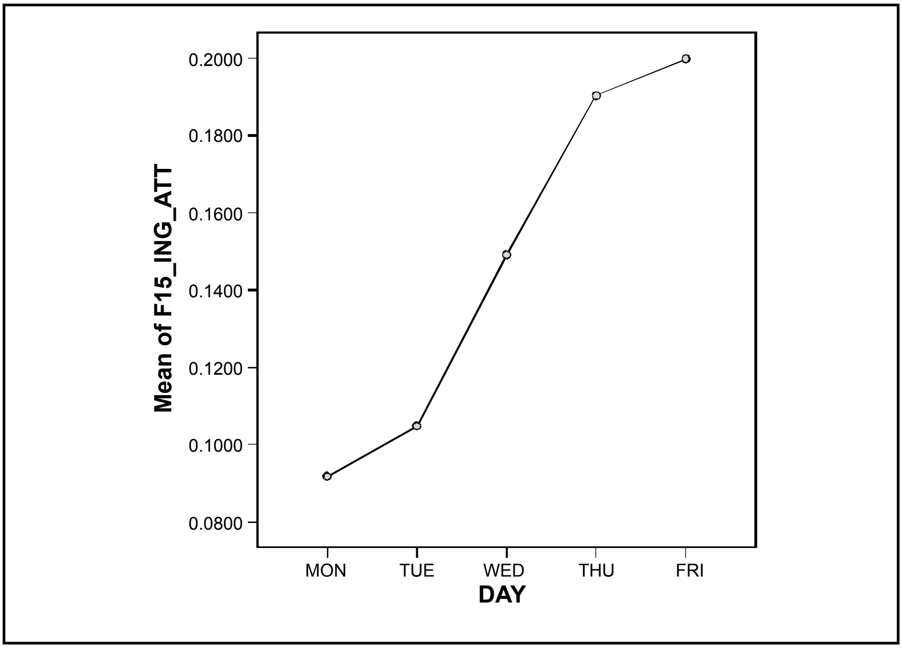
RED_ING_ATT

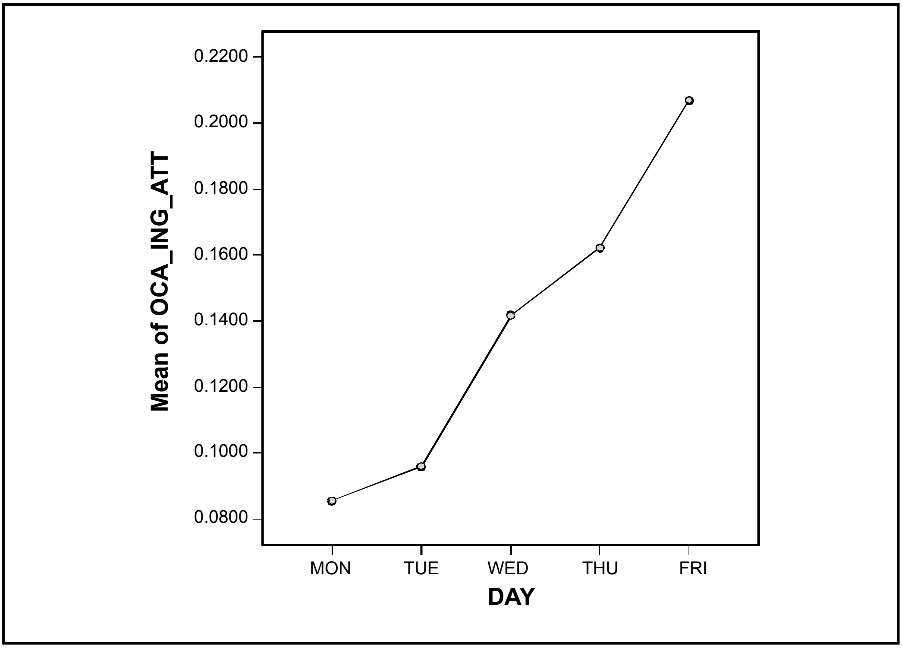
Tukey HSD

DAY2	N	Subset for alpha = .05
		1
THU	36	.681468
TUE	37	.724625
WED	36	.726546
MON	38	.773405
FRI	20	.777895
Sig.		.439

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 31.467.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots

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0.2000
0.1800
0.1600
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0.1200
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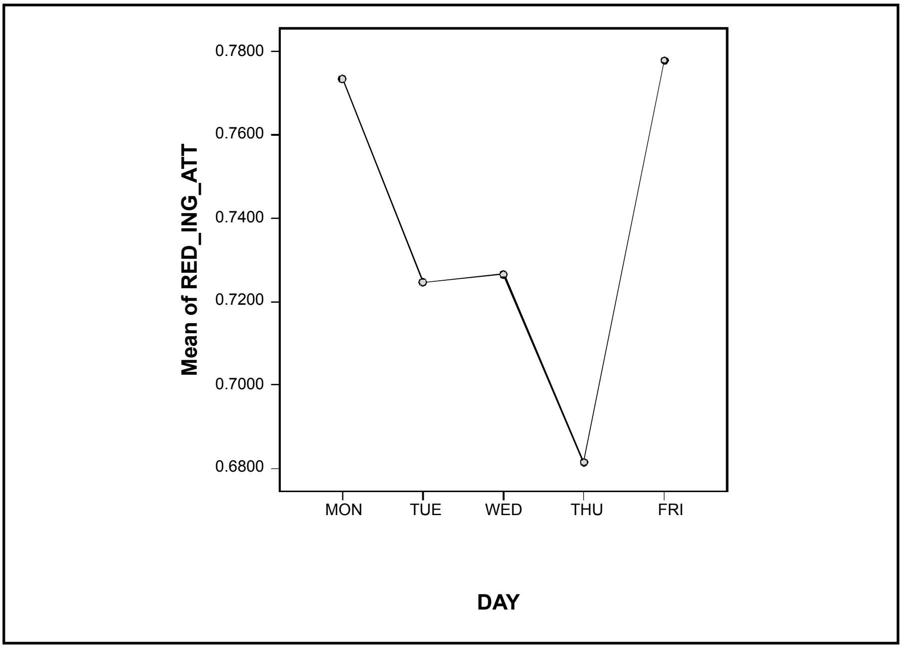
Mean of OCA_ING_ATT
MON
TUE
WED
THU
FRI
DAY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0.7000
0.6800
Mean of RED_ING_ATT
MON
TUE
WED
THU
FRI
DAY

Univariate Analysis of Variance–F-15C Attrition

Between-Subjects Factors

		Value Label	N
DAY2	1	MON	41
	2	TUE	68
	3	WED	71
	4	THU	70
	5	FRI	49
WK	1		140
	2		159

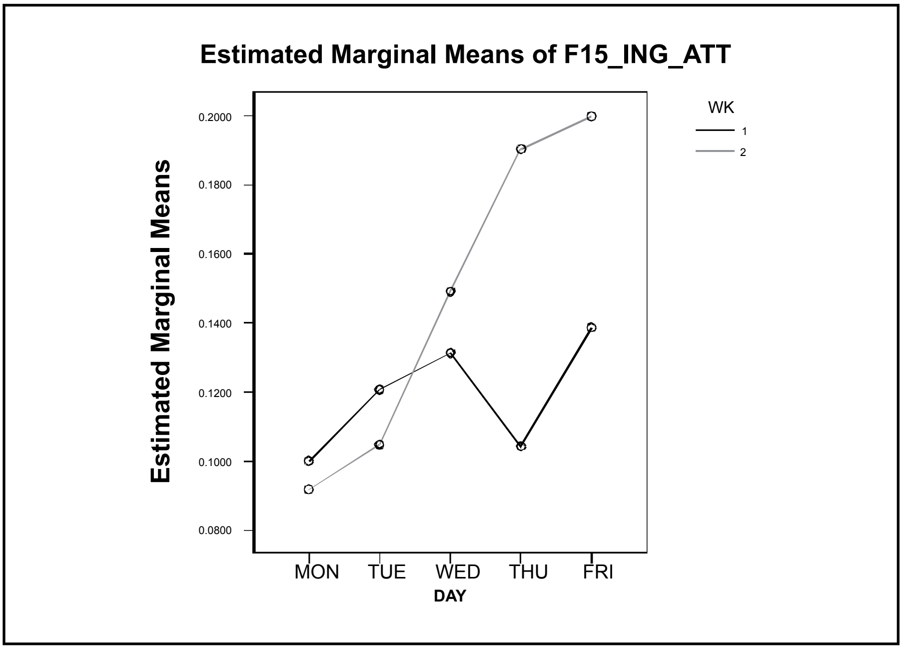
Tests of Between-Subjects Effects

Dependent Variable: F15_ING_ATT

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Corrected Model	.324(a)	9	.036	1.572	.123
Intercept	3.263	1	3.263	142.559	.000
DAY2	.117	4	.029	1.276	.280
WK	.037	1	.037	1.597	.207
DAY2 * WK	.108	4	.027	1.185	.318
Error	6.614	289	.023		
Total	12.117	299			
Corrected Total	6.938	298			

a R Squared = .047 (Adjusted R Squared = .017)

Profile Plots



Univariate Analysis of Variance-Red Air Attrition

Between-Subjects Factors

		Value Label	N
DAY2	1	MON	42
	2	TUE	68
	3	WED	72
	4	THU	72
	5	FRI	53
WK	1		140
	2		167

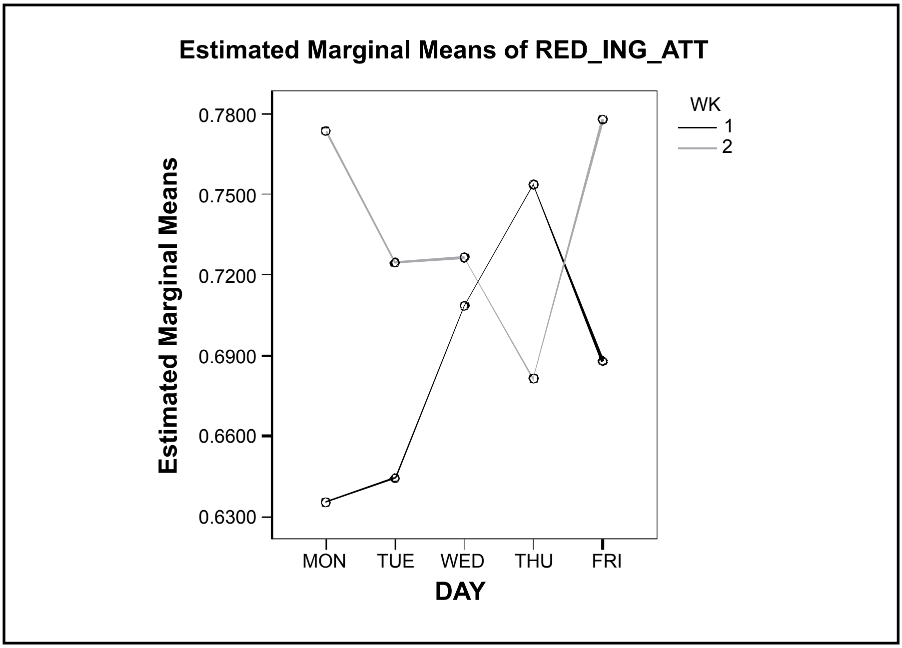
Tests of Between-Subjects Effects

Dependent Variable: RED_ING_ATT

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Corrected Model	.514(a)	9	.057	1.147	.329
Intercept	96.023	1	96.023	1927.284	.000
DAY2	.078	4	.019	.390	.816
WK	.123	1	.123	2.460	.118
DAY2 * WK	.320	4	.080	1.604	.173
Error	14.797	297	.050		
Total	173.398	307			
Corrected Total	15.312	306			

a R Squared = .034 (Adjusted R Squared = .004)

Profile Plots



A4. Day-Night Independent Samples T-test

Author's original work using SPSS 12.0.1

Group Statistics

	LIGHT	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	DAY	185	.145597	.1589280	.0116846
	NIGHT	114	.108928	.1393907	.0130551
OCA_ING_ATT	DAY	190	.133635	.1439208	.0104411
	NIGHT	117	.105587	.1320833	.0122111
RED_ING_ATT	DAY	190	.693107	.2195623	.0159287
	NIGHT	117	.757356	.2255554	.0208526

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	5.253	.023	2.029	297	.043	.0366686	.0180736	.0011000	.0722371
	Equal variances not assumed			2.093	262.933	.037	.0366686	.0175205	.0021703	.0711668
OCA_ING_ATT	Equal variances assumed	2.234	.136	1.710	305	.088	.0280486	.0163979	-.0042188	.0603160
	Equal variances not assumed			1.746	261.751	.082	.0280486	.0160664	-.0035871	.0596844
RED_ING_ATT	Equal variances assumed	.801	.371	-2.464	305	.014	-.0642494	.0260723	-.1155539	-.0129450
	Equal variances not assumed			-2.448	240.591	.015	-.0642494	.0262403	-.1159396	-.0125593

A5. Threat Aircraft ANOVA

Author's original work using SPSS 12.0.1

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Mini-mum	Maxi-mum
						Lower Bound	Upper Bound		
F15_ING_ATT	MiG-23	34	.073214	.1245783	.0213650	.029747	.116682	.0000	.4286
	MiG-29	141	.115802	.1453636	.0122418	.091599	.140005	.0000	.7500
	SU-27	124	.165611	.1606120	.0144234	.137061	.194162	.0000	.7500
	Total	299	.131616	.1525829	.0088241	.114251	.148981	.0000	.7500
OCA_ING_ATT	MiG-23	34	.073214	.1245783	.0213650	.029747	.116682	.0000	.4286
	MiG-29	142	.106489	.1305409	.0109548	.084832	.128145	.0000	.7500
	SU-27	131	.153692	.1476529	.0129005	.128170	.179215	.0000	.7500
	Total	307	.122946	.1399754	.0079888	.107226	.138666	.0000	.7500
RED_ING_ATT	MiG-23	34	.751471	.2415154	.0414196	.667202	.835739	.0000	1.0000
	MiG-29	142	.717246	.2228020	.0186971	.680283	.754208	.0000	1.1250
	SU-27	131	.709176	.2208224	.0192933	.671007	.747346	.1111	1.0000
	Total	307	.717593	.2236921	.0127668	.692471	.742714	.0000	1.1250

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	1.625	2	296	.199
OCA_ING_ATT	1.695	2	304	.185
RED_ING_ATT	.024	2	304	.976

ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.295	2	.147	6.562	.002
	Within Groups	6.643	296	.022		
	Total	6.938	298			
OCA_ING_ATT	Between Groups	.246	2	.123	6.514	.002
	Within Groups	5.749	304	.019		
	Total	5.995	306			
RED_ING_ATT	Between Groups	.048	2	.024	.481	.619
	Within Groups	15.263	304	.050		
	Total	15.312	306			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) THRT_AC	(J) THRT_AC	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_ING_ATT	MiG-23	MiG-29	-.0425879	.0286232	.298	-.110012	.024836
		SU-27	-.0923971(*)	.0290019	.005	-.160713	-.024081
	MiG-29	MiG-23	.0425879	.0286232	.298	-.024836	.110012
		SU-27	-.0498092(*)	.0184438	.020	-.093255	-.006364
	SU-27	MiG-23	.0923971(*)	.0290019	.005	.024081	.160713
		MiG-29	.0498092(*)	.0184438	.020	.006364	.093255
OCA_ING_ATT	MiG-23	MiG-29	-.0332743	.0262564	.415	-.095115	.028566
		SU-27	-.0804782(*)	.0264686	.007	-.142818	-.018138
	MiG-29	MiG-23	.0332743	.0262564	.415	-.028566	.095115
		SU-27	-.0472039(*)	.0166596	.014	-.086441	-.007966
	SU-27	MiG-23	.0804782(*)	.0264686	.007	.018138	.142818
		MiG-29	.0472039(*)	.0166596	.014	.007966	.086441
RED_ING_ATT	MiG-23	MiG-29	.0342250	.0427820	.703	-.066537	.134987
		SU-27	.0422944	.0431276	.590	-.059282	.143871
	MiG-29	MiG-23	-.0342250	.0427820	.703	-.134987	.066537
		SU-27	.0080694	.0271450	.952	-.055864	.072003
	SU-27	MiG-23	-.0422944	.0431276	.590	-.143871	.059282
		MiG-29	-.0080694	.0271450	.952	-.072003	.055864

* The mean difference is significant at the .05 level.

Homogeneous Subsets

F15_ING_ATT

Tukey HSD

THRT_AC	N	Subset for alpha = .05	
		1	2
MiG-23	34	.073214	
MiG-29	141	.115802	.115802
SU-27	124		.165611
Sig.		.227	.132

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 67.312.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_ING_ATT

Tukey HSD

THRT_AC	N	Subset for alpha = .05	
		1	2
MiG-23	34	.073214	
MiG-29	142	.106489	.106489
SU-27	131		.153692
Sig.		.336	.113

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 68.046.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

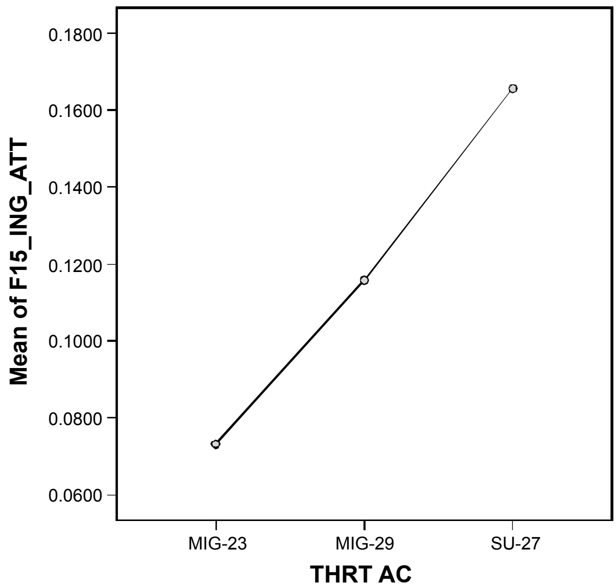
RED_ING_ATT

Tukey HSD

THRT_AC	N	Subset for alpha = .05
		1
SU-27	131	.709176
MIG-29	142	.717246
MiG-23	34	.751471
Sig.		.514

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 68.046.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots



Mean of F15_ING_ATT
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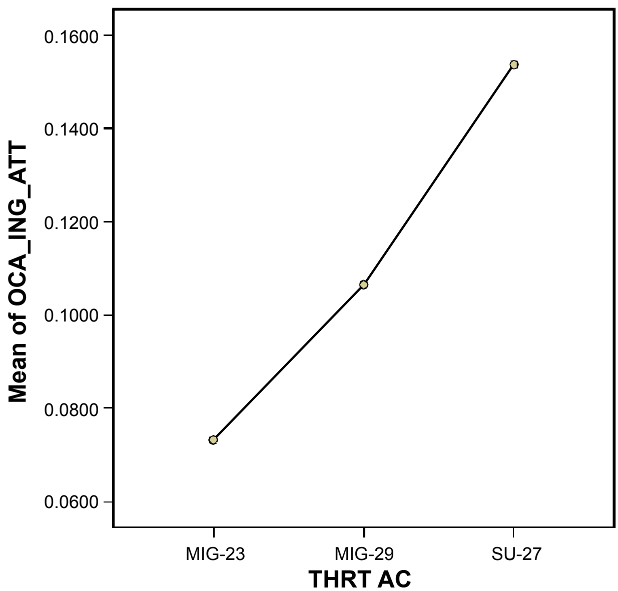
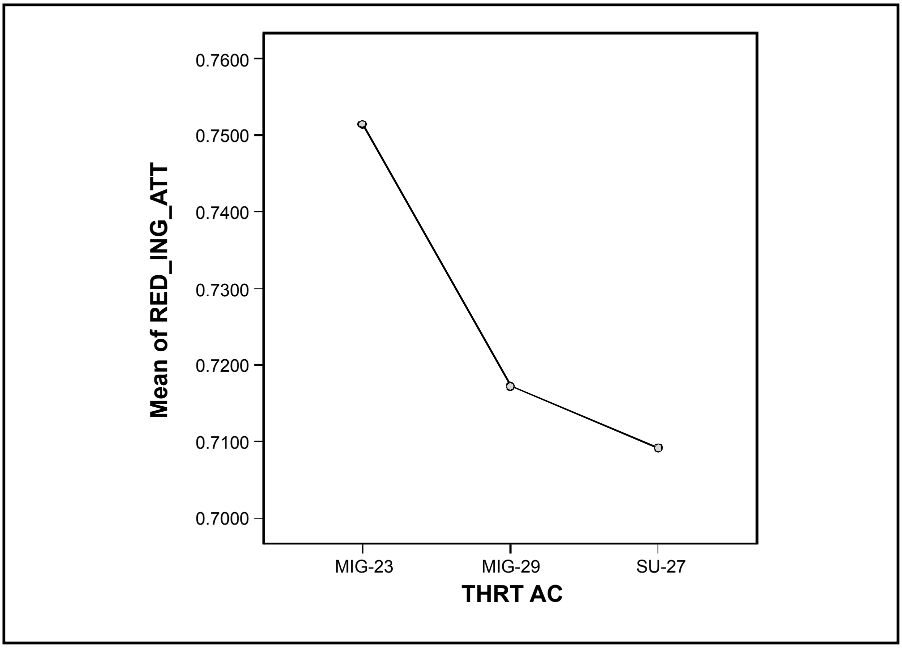
0.1400
0.1200
0.1000
0.0800
0.0600
MIG-23
MIG-29
SU-27
THRT AC



Mean of OCA_ING_ATT
0.1600
0.1400
0.1200
0.1000
0.0800
0.0600
MIG-23
MIG-29
SU-27
THRT AC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0.7400
0.7300
0.7200
0.7100
0.7000
Mean of RED_ING_ATT
MIG-23
MIG-29
SU-27
THRT AC

A6. Threat Weapons T-test
Author's original work using SPSS 12.0.1

Group Statistics

	WEAPON2	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	SHORT	227	.117505	.1409548	.0093555
	LONG	72	.176104	.1784115	.0210260
OCA_ING_ATT	SHORT	228	.108016	.1272607	.0084280
	LONG	79	.166034	.1649272	.0185558
RED_ING_ATT	SHORT	228	.714948	.2232472	.0147849
	LONG	79	.725225	.2262275	.0254526

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	4.010	.046	-2.874	297	.004	-.0585981	.0203909	-.0987271	-.0184691
	Equal variances not assumed			-2.546	100.657	.012	-.0585981	.0230134	-.1042525	-.0129438
OCA_ING_ATT	Equal variances assumed	6.344	.012	-3.223	305	.001	-.0580178	.0180002	-.0934381	-.0225975
	Equal variances not assumed			-2.847	111.866	.005	-.0580178	.0203801	-.0983989	-.0176368
RED_ING_ATT	Equal variances assumed	.038	.845	-.351	305	.726	-.0102764	.0292457	-.0678253	.0472724
	Equal variances not assumed			-.349	134.266	.728	-.0102764	.0294351	-.0684930	.0479401

Univariate Analysis of Variance

Between-Subjects Factors

		Value Label	N
WEAPON2	2	SHORT	227
	3	LONG	72
THRT_AC	3	MiG-23	34
	4	MiG-29	141
	5	SU-27	124

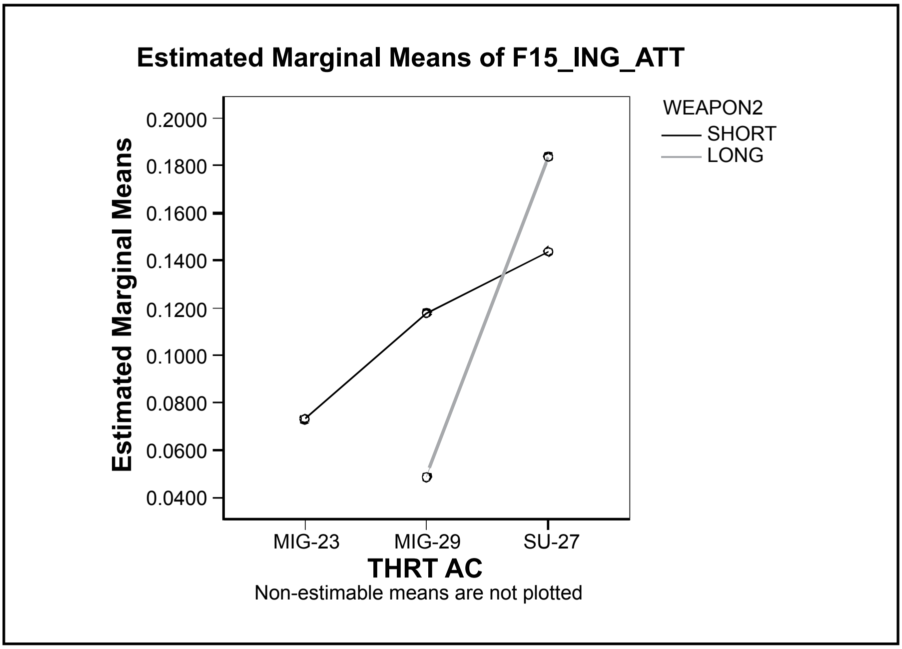
Tests of Between-Subjects Effects

Dependent Variable: F15_ING_ATT

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Corrected Model	.362(a)	4	.090	4.044	.003
Intercept	.733	1	.733	32.771	.000
WEAPON2	.003	1	.003	.133	.716
THRT_AC	.173	2	.087	3.872	.022
WEAPON2 * THRT_AC	.041	1	.041	1.832	.177
Error	6.576	294	.022		
Total	12.117	299			
Corrected Total	6.938	298			

a R Squared = .052 (Adjusted R Squared = .039)

Profile Plots



One Way

Warnings

Post-hoc tests are not performed for F15_ING_ATT because there are fewer than three groups.

Post-hoc tests are not performed for OCA_ING_ATT because there are fewer than three groups.

Post-hoc tests are not performed for RED_ING_ATT because there are fewer than three groups.

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Mini-mum	Maxi-mum
						Lower Bound	Upper Bound		
F15_ING_ATT	SHORT	227	.117505	.1409548	.0093555	.099070	.135941	.0000	.7500
	LONG	72	.176104	.1784115	.0210260	.134179	.218028	.0000	.7500
	Total	299	.131616	.1525829	.0088241	.114251	.148981	.0000	.7500
OCA_ING_ATT	SHORT	228	.108016	.1272607	.0084280	.091409	.124623	.0000	.7500
	LONG	79	.166034	.1649272	.0185558	.129092	.202976	.0000	.7500
	Total	307	.122946	.1399754	.0079888	.107226	.138666	.0000	.7500
RED_ING_ATT	SHORT	228	.714948	.2232472	.0147849	.685815	.744081	.0000	1.1250
	LONG	79	.725225	.2262275	.0254526	.674552	.775897	.1111	1.0000
	Total	307	.717593	.2236921	.0127668	.692471	.742714	.0000	1.1250

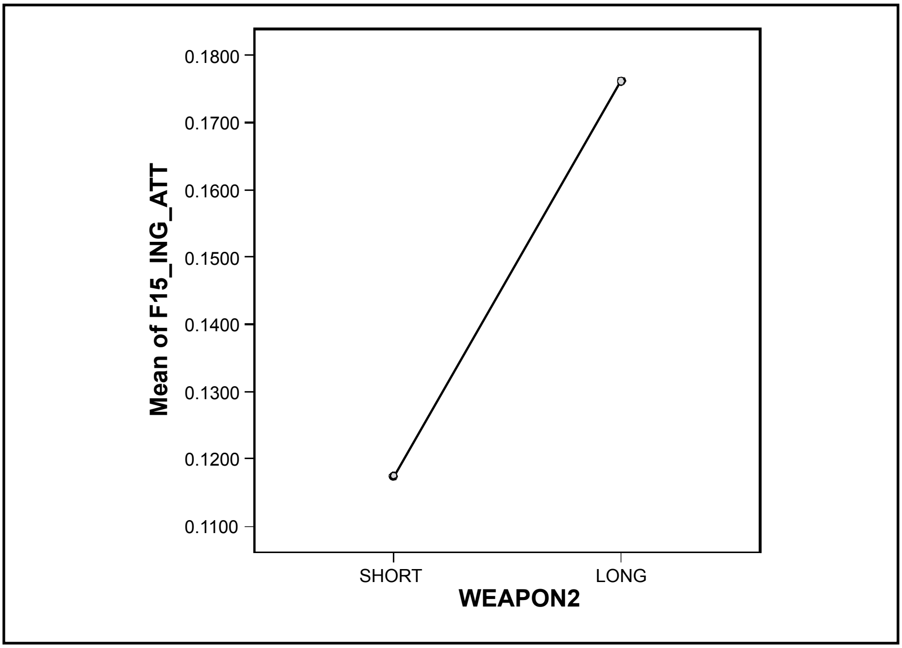
Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	4.010	1	297	.046
OCA_ING_ATT	6.344	1	305	.012
RED_ING_ATT	.038	1	305	.845

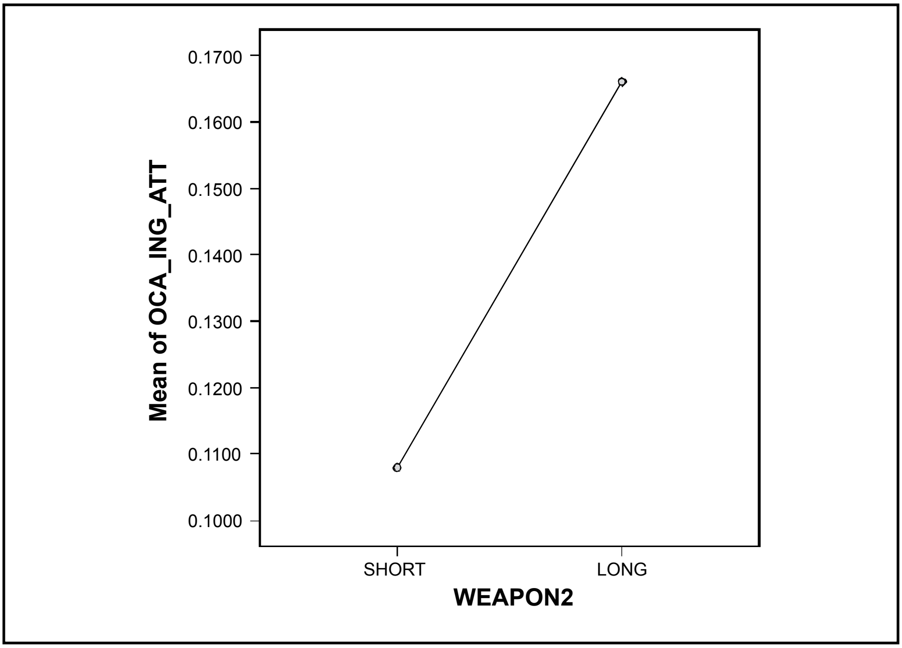
ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.188	1	.188	8.258	.004
	Within Groups	6.750	297	.023		
	Total	6.938	298			
OCA_ING_ATT	Between Groups	.197	1	.197	10.389	.001
	Within Groups	5.798	305	.019		
	Total	5.995	306			
RED_ING_ATT	Between Groups	.006	1	.006	.123	.726
	Within Groups	15.305	305	.050		
	Total	15.312	306			

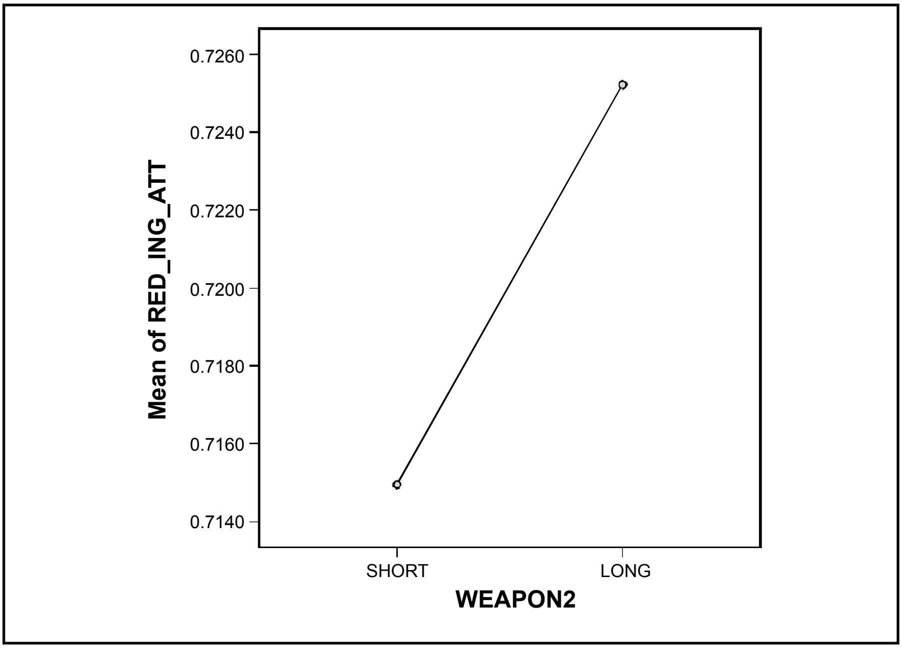
Means Plots



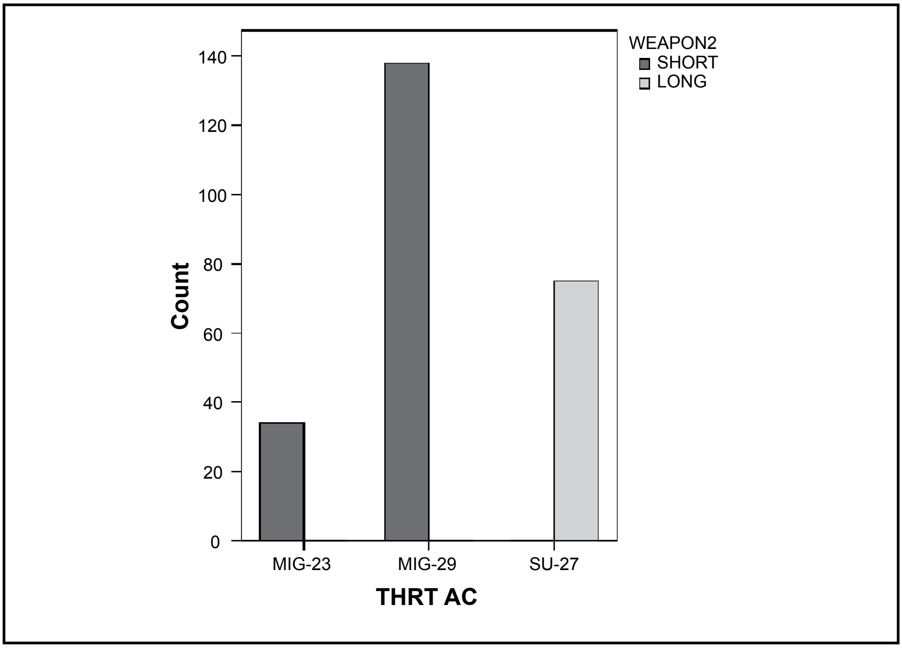
APPENDIX A



0.1700
0.1600
0.1500
0.1400
0.1300
0.1200
0.1100
0.1000
Mean of OCA_ING_ATT
SHORT
LONG
WEAPON2



0.7260
0.7240
0.7220
0.7200
0.7180
0.7160
0.7140
Mean of RED_ING_ATT
SHORT
LONG
WEAPON2


Count
140
120
100
80
60
40
20
0
MIG-23
MIG-29
SU-27
THRT AC
WEAPON2
SHORT
LONG

One Way

Warnings

Post-hoc tests are not performed for F15_ING_ATT because there are fewer than three groups.
Post-hoc tests are not performed for OCA_ING_ATT because there are fewer than three groups.
Post-hoc tests are not performed for RED_ING_ATT because there are fewer than three groups.

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
F15_ING_ATT	SHORT	171	.108906	.1434054	.0109665	.087258	.130554	.0000	.7500
	LONG	68	.183603	.1804347	.0218809	.139929	.227278	.0000	.7500
	Total	239	.130159	.1580984	.0102265	.110013	.150305	.0000	.7500
OCA_ING_ATT	SHORT	172	.101257	.1307787	.0099718	.081573	.120941	.0000	.7500
	LONG	75	.172297	.1665932	.0192365	.133967	.210626	.0000	.7500
	Total	247	.122828	.1459749	.0092882	.104533	.141122	.0000	.7500
RED_ING_ATT	SHORT	172	.726931	.2277614	.0173666	.692651	.761212	.0000	1.1250
	LONG	75	.732348	.2296481	.0265175	.679511	.785185	.1111	1.0000
	Total	247	.728576	.2278820	.0144998	.700016	.757136	.0000	1.1250

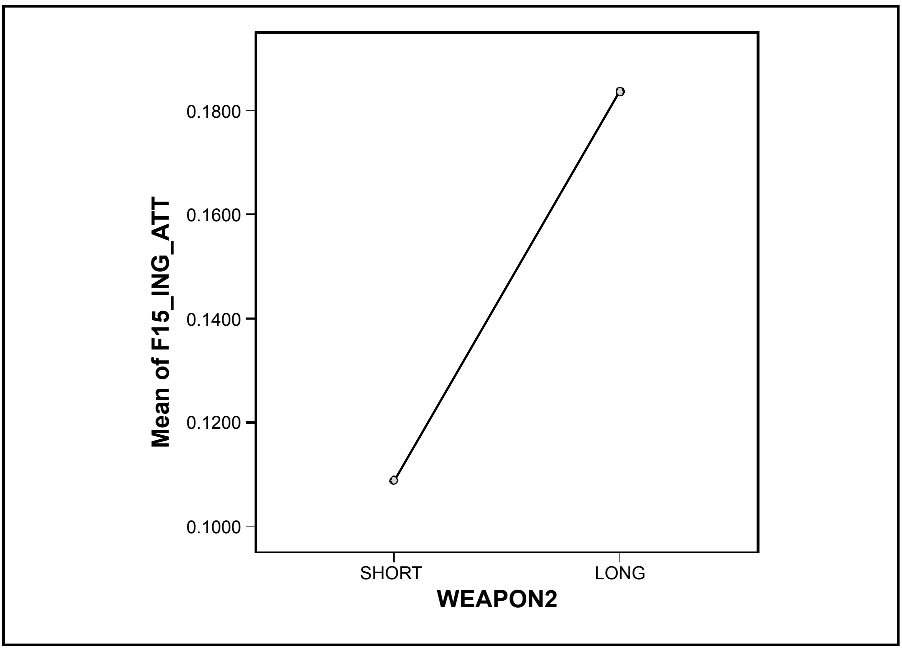
Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	3.983	1	237	.047
OCA_ING_ATT	5.856	1	245	.016
RED_ING_ATT	.025	1	245	.874

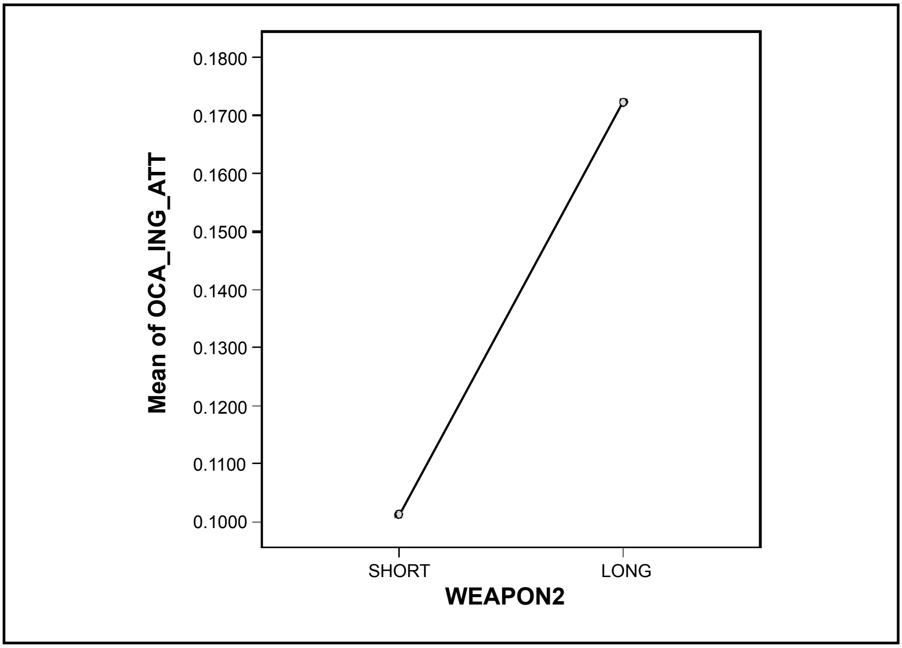
ANOVA

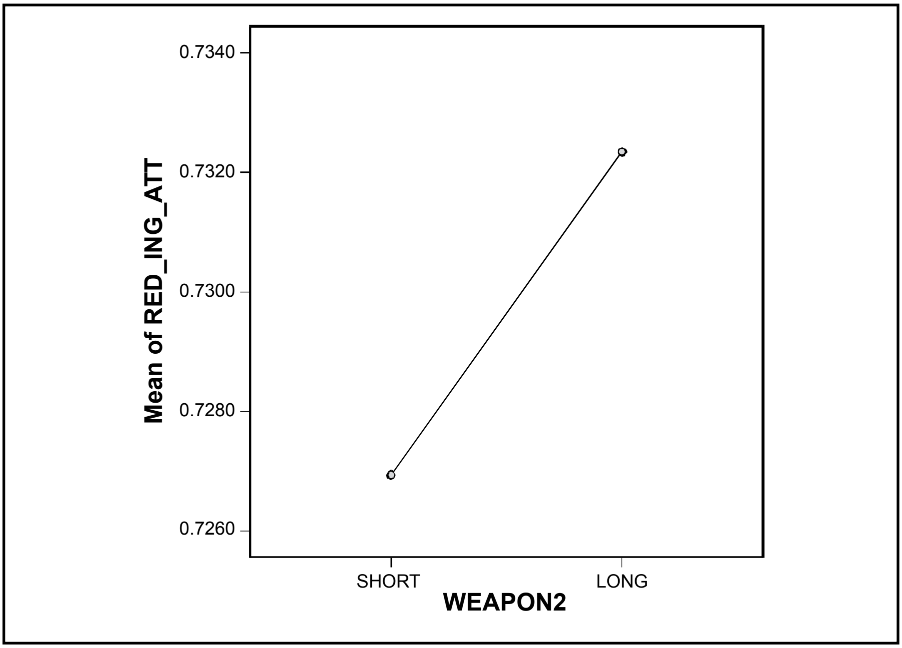
		Sum of Squares	df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.271	1	.271	11.332	.001
	Within Groups	5.677	237	.024		
	Total	5.948	238			
OCA_ING_ATT	Between Groups	.264	1	.264	12.971	.000
	Within Groups	4.978	245	.020		
	Total	5.242	246			
RED_ING_ATT	Between Groups	.002	1	.002	.029	.864
	Within Groups	12.773	245	.052		
	Total	12.775	246			

Means Plots



APPENDIX A


0.1800
0.1700
0.1600
0.1500
0.1400
0.1300
0.1200
0.1100
0.1000
Mean of OCA_ING_ATT
SHORT
LONG
WEAPON2


0.7340
0.7320
0.7300
0.7280
0.7260
Mean of RED_ING_ATT
SHORT
LONG
WEAPON2

Correlations

Correlations

		THRT_AC	WEAPON2
THRT_AC	Pearson Correlation	1	.564(**)
	Sig. (2-tailed)		.000
	N	307	307
WEAPON2	Pearson Correlation	.564(**)	1
	Sig. (2-tailed)	.000	
	N	307	307

** Correlation is significant at the 0.01 level (2-tailed).

A7. Aircraft and Weapons ANOVA

Author’s original work using SPSS 12.0.1

Short Only

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Mini-mum	Maxi-mum
						Lower Bound	Upper Bound		
F15_ING_ATT	MiG-23	34	.073214	.1245783	.0213650	.029747	.116682	.0000	.4286
	MiG-29	147	.122143	.1503563	.0124012	.097634	.146652	.0000	.7500
	SU-27	56	.143764	.1309335	.0174967	.108700	.178828	.0000	.3750
	Total	237	.120233	.1435386	.0093238	.101864	.138601	.0000	.7500
OCA_ING_ATT	MiG-23	34	.073214	.1245783	.0213650	.029747	.116682	.0000	.4286
	MiG-29	147	.112801	.1375646	.0113461	.090377	.135225	.0000	.7500
	SU-27	56	.128776	.1143925	.0152863	.098142	.159411	.0000	.3750
	Total	237	.110896	.1311857	.0085214	.094109	.127684	.0000	.7500
RED_ING_ATT	MiG-23	34	.751471	.2415154	.0414196	.667202	.835739	.0000	1.0000
	MiG-29	147	.727339	.2156728	.0177884	.692183	.762495	.0000	1.1667
	SU-27	56	.678143	.2063667	.0275769	.622877	.733408	.2727	1.0000
	Total	237	.719177	.2178271	.0141494	.691301	.747052	.0000	1.1667

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
F15_ING_ATT	.424	2	234	.655
OCA_ING_ATT	.131	2	234	.877
RED_ING_ATT	.298	2	234	.743

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
F15_ING_ATT	Between Groups	.107	2	.053	2.625	.075
	Within Groups	4.756	234	.020		
	Total	4.863	236			
OCA_ING_ATT	Between Groups	.067	2	.033	1.954	.144
	Within Groups	3.995	234	.017		
	Total	4.062	236			
RED_ING_ATT	Between Groups	.140	2	.070	1.476	.231
	Within Groups	11.058	234	.047		
	Total	11.198	236			

Post-Hoc Tests

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) THRT_AC	(J) THRT_AC	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
F15_ING_ATT	MiG-23	MiG-29	-.0489292	.0271293	.171	-.112920	.015062
		SU-27	-.0705499	.0309946	.061	-.143658	.002558
	MiG-29	MiG-23	.0489292	.0271293	.171	-.015062	.112920
		SU-27	-.0216207	.0223869	.599	-.074425	.031184
	SU-27	MiG-23	.0705499	.0309946	.061	-.002558	.143658
		MiG-29	.0216207	.0223869	.599	-.031184	.074425
OCA_ING_ATT	MiG-23	MiG-29	-.0395863	.0248645	.251	-.098235	.019062
		SU-27	-.0555620	.0284070	.126	-.122566	.011442
	MiG-29	MiG-23	.0395863	.0248645	.251	-.019062	.098235
		SU-27	-.0159756	.0205179	.717	-.064372	.032420
	SU-27	MiG-23	.0555620	.0284070	.126	-.011442	.122566
		MiG-29	.0159756	.0205179	.717	-.032420	.064372
RED_ING_ATT	MiG-23	MiG-29	.0241312	.0413693	.829	-.073448	.121710
		SU-27	.0733278	.0472634	.269	-.038153	.184809
	MiG-29	MiG-23	-.0241312	.0413693	.829	-.121710	.073448
		SU-27	.0491966	.0341375	.322	-.031324	.129718
	SU-27	MiG-23	-.0733278	.0472634	.269	-.184809	.038153
		MiG-29	-.0491966	.0341375	.322	-.129718	.031324

Homogeneous Subsets

F15_ING_ATT

Tukey HSD

THRT_AC	N	Subset for alpha = .05	
		1	2
MiG-23	34	.073214	
MiG-29	147	.122143	.122143
SU-27	56		.143764
Sig.		.169	.704

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 55.482.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

OCA_ING_ATT

Tukey HSD

THRT_AC	N	Subset for alpha = .05
		1
MiG-23	34	.073214
MiG-29	147	.112801
SU-27	56	.128776
Sig.		.067

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 55.482.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

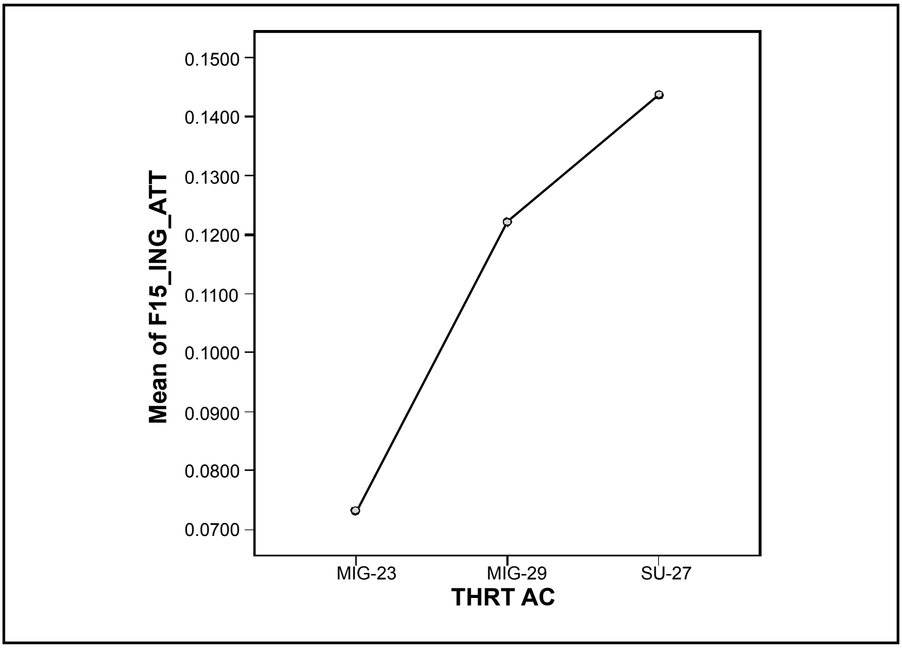
RED_ING_ATT

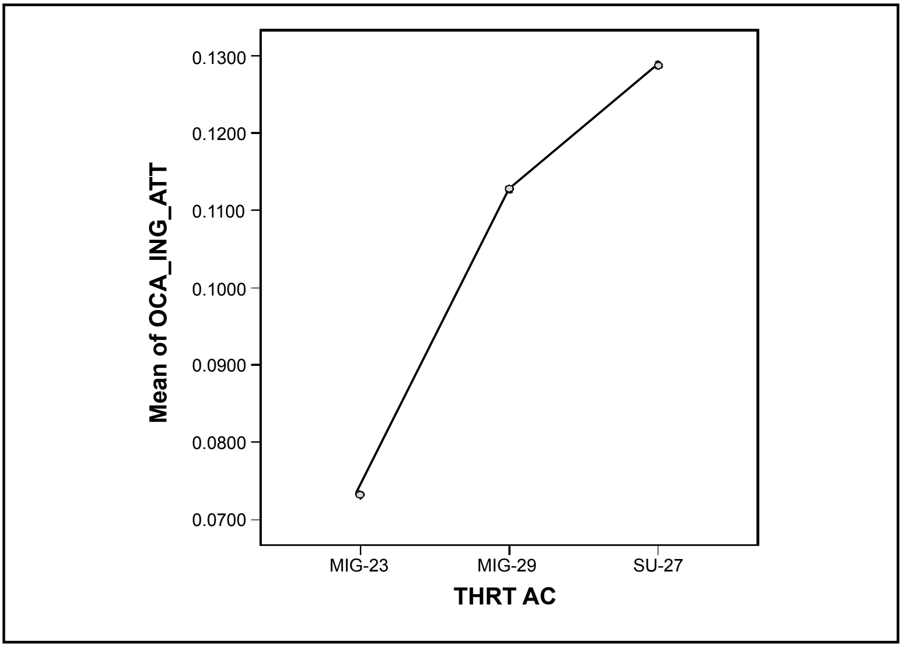
Tukey HSD

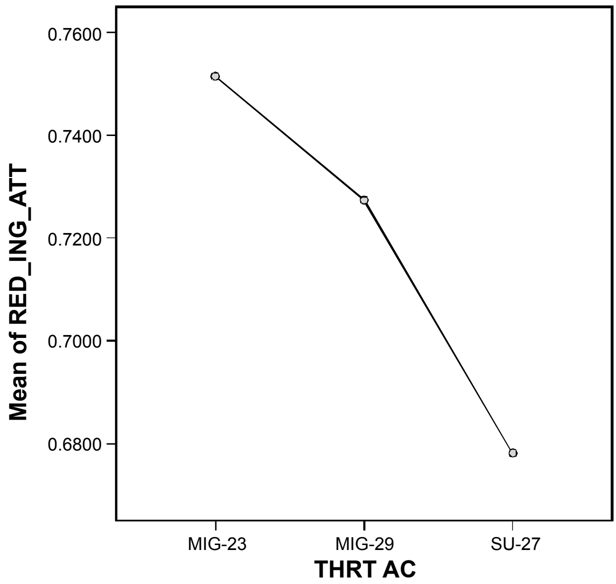
THRT_AC	N	Subset for alpha = .05
		1
SU-27	56	.678143
MiG-29	147	.727339
MiG-23	34	.751471
Sig.		.180

Means for groups in homogeneous subsets are displayed.
a Uses Harmonic Mean Sample Size = 55.482.
b The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Means Plots


0.1500
0.1400
0.1300
0.1200
0.1100
0.1000
0.0900
0.0800
0.0700
Mean of F15_ING_ATT
MIG-23
MIG-29
SU-27
THRT AC


0.1300
0.1200
0.1100
0.1000
0.0900
0.0800
0.0700
Mean of OCA_ING_ATT
MIG-23
MIG-29
SU-27
THRT AC


0.7600
0.7400
0.7200
0.7000
0.6800
Mean of RED_ING_ATT
MIG-23
MIG-29
SU-27
THRT AC

T-test Short Only

Group Statistics

	THRT_AC	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	MiG-29	147	.122143	.1503563	.0124012
	SU-27	56	.143764	.1309335	.0174967
OCA_ING_ATT	MiG-29	147	.112801	.1375646	.0113461
	SU-27	56	.128776	.1143925	.0152863
RED_ING_ATT	MiG-29	147	.727339	.2156728	.0177884
	SU-27	56	.678143	.2063667	.0275769

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	.016	.899	-.948	201	.344	-.0216207	.0228171	-.0666123	.0233709
	Equal variances not assumed			-1.008	113.362	.316	-.0216207	.0214459	-.0641074	.0208659
OCA_ING_ATT	Equal variances assumed	.194	.660	-.773	201	.441	-.0159756	.0206705	-.0567344	.0247831
	Equal variances not assumed			-.839	118.720	.403	-.0159756	.0190370	-.0536717	.0217204
RED_ING_ATT	Equal variances assumed	.284	.595	1.470	201	.143	.0491966	.0334746	-.0168097	.1152030
	Equal variances not assumed			1.499	103.539	.137	.0491966	.0328164	-.0158828	.1142761

T-test MiG–29 Only

Group Statistics

	WEAPON2	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	SHORT	147	.122143	.1503563	.0124012
	LONG	4	.048611	.0572654	.0286327
OCA_ING_ATT	SHORT	147	.112801	.1375646	.0113461
	LONG	4	.048611	.0572654	.0286327
RED_ING_ATT	SHORT	147	.727339	.2156728	.0177884
	LONG	4	.591667	.0687184	.0343592

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.817	.180	.973	149	.332	.0735323	.0755355	-.0757268	.2227915
	Equal variances not assumed			2.357	4.228	.074	.0735323	.0312029	-.0112888	.1583535
OCA_ING_ATT	Equal variances assumed	1.552	.215	.929	149	.355	.0641895	.0691292	-.0724107	.2007898
	Equal variances not assumed			2.084	4.014	.105	.0641895	.0307988	-.0212033	.1495824
RED_ING_ATT	Equal variances assumed	4.915	.028	1.253	149	.212	.1356727	.1083007	-.0783308	.3496762
	Equal variances not assumed			3.507	4.817	.018	.1356727	.0386909	.0350648	.2362806

T-test SU–27 Only

Group Statistics

	WEAPON2	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	SHORT	56	.143764	.1309335	.0174967
	LONG	120	.165708	.1639277	.0149645
OCA_ING_ATT	SHORT	56	.128776	.1143925	.0152863
	LONG	120	.152881	.1470661	.0134252
RED_ING_ATT	SHORT	56	.678143	.2063667	.0275769
	LONG	120	.736021	.2264059	.0206679

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.105	.295	-.879	174	.381	-.0219443	.0249651	-.0712177	.0273292
	Equal variances not assumed			-.953	132.200	.342	-.0219443	.0230233	-.0674859	.0235974
OCA_ING_ATT	Equal variances assumed	1.337	.249	-1.083	174	.280	-.0241048	.0222651	-.0680493	.0198398
	Equal variances not assumed			-1.185	135.350	.238	-.0241048	.0203448	-.0643395	.0161300
RED_ING_ATT	Equal variances assumed	.178	.674	-1.624	174	.106	-.0578785	.0356471	-.1282349	.0124780
	Equal variances not assumed			-1.679	117.068	.096	-.0578785	.0344623	-.1261288	.0103719

T-test MiG–29/Short versus Long SU-27

Group Statistics

	THRT_AC	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	MiG-29	147	.122143	.1503563	.0124012
	SU-27	120	.165708	.1639277	.0149645
OCA_ING_ATT	MiG-29	147	.112801	.1375646	.0113461
	SU-27	120	.152881	.1470661	.0134252
RED_ING_ATT	MiG-29	147	.727339	.2156728	.0177884
	SU-27	120	.736021	.2264059	.0206679

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.280	.259	-2.261	265	.025	-.0435650	.0192658	-.0814986	-.0056314
	Equal variances not assumed			-2.242	244.560	.026	-.0435650	.0194352	-.0818466	-.0052833
OCA_ING_ATT	Equal variances assumed	.773	.380	-2.296	265	.022	-.0400804	.0174590	-.0744564	-.0057044
	Equal variances not assumed			-2.280	246.997	.023	-.0400804	.0175776	-.0747015	-.0054593
RED_ING_ATT	Equal variances assumed	.003	.955	-.320	265	.749	-.0086818	.0271349	-.0621092	.0447455
	Equal variances not assumed			-.318	249.162	.750	-.0086818	.0272689	-.0623887	.0450250

T-test MiG–23 and MiG–29 Short versus Long SU-27

Group Statistics

	WEAPON2	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	SHORT	181	.112952	.1467970	.0109113
	LONG	120	.165708	.1639277	.0149645
OCA_ING_ATT	SHORT	181	.105365	.1357762	.0100922
	LONG	120	.152881	.1470661	.0134252
RED_ING_ATT	SHORT	181	.731872	.2202539	.0163713
	LONG	120	.736021	.2264059	.0206679

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.453	.229	-2.913	299	.004	-.0527561	.0181106	-.0883965	-.0171157
	Equal variances not assumed			-2.849	235.216	.005	-.0527561	.0185201	-.0892425	-.0162697
OCA_ING_ATT	Equal variances assumed	.731	.393	-2.875	299	.004	-.0475165	.0165255	-.0800375	-.0149956
	Equal variances not assumed			-2.829	240.683	.005	-.0475165	.0167955	-.0806015	-.0144316
RED_ING_ATT	Equal variances assumed	.055	.815	-.158	299	.874	-.0041489	.0262191	-.0557462	.0474484
	Equal variances not assumed			-.157	250.089	.875	-.0041489	.0263663	-.0560773	.0477795

A8.T-test

Author's original work using SPSS 12.0.1

Group Statistics

	WEAPON2	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	SHORT	181	.112952	.1467970	.0109113
	LONG	120	.165708	.1639277	.0149645
OCA_ING_ATT	SHORT	181	.105365	.1357762	.0100922
	LONG	120	.152881	.1470661	.0134252
RED_ING_ATT	SHORT	181	.731872	.2202539	.0163713
	LONG	120	.736021	.2264059	.0206679

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.453	.229	-2.913	299	.004	-.0527561	.0181106	-.0883965	-.0171157
	Equal variances not assumed			-2.849	235.216	.005	-.0527561	.0185201	-.0892425	-.0162697
OCA_ING_ATT	Equal variances assumed	.731	.393	-2.875	299	.004	-.0475165	.0165255	-.0800375	-.0149956
	Equal variances not assumed			-2.829	240.683	.005	-.0475165	.0167955	-.0806015	-.0144316
RED_ING_ATT	Equal variances assumed	.055	.815	-.158	299	.874	-.0041489	.0262191	-.0557462	.0474484
	Equal variances not assumed			-.157	250.089	.875	-.0041489	.0263663	-.0560773	.0477795

T-test

Group Statistics

	LIGHT	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	DAY	178	.150025	.1637746	.0122754
	NIGHT	123	.110772	.1407805	.0126937
OCA_ING_ATT	DAY	178	.138753	.1481119	.0111015
	NIGHT	123	.103403	.1306123	.0117769
RED_ING_ATT	DAY	178	.717010	.2134606	.0159995
	NIGHT	123	.757429	.2334584	.0210502

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	4.849	.028	2.163	299	.031	.0392530	.0181513	.0035326	.0749734
	Equal variances not assumed			2.223	285.050	.027	.0392530	.0176584	.0044957	.0740103
OCA_ING_ATT	Equal variances assumed	2.562	.111	2.135	299	.034	.0353498	.0165600	.0027610	.0679387
	Equal variances not assumed			2.184	281.786	.030	.0353498	.0161845	.0034920	.0672077
RED_ING_ATT	Equal variances assumed	1.719	.191	-1.554	299	.121	-.0404192	.0260110	-.0916070	.0107686
	Equal variances not assumed			-1.529	246.883	.128	-.0404192	.0264405	-.0924968	.0116584

A9. Red Tactics Pearson Correlation Test

Author's original work using SPSS 12.0.1

Correlations

		TACTIC2	EA2	REGEN	RXN_LVL	MAX_LIVE_ GRPS	SAM_LVL	SAM_ ROE2	REC	BIG_ CROW2
TACTIC2	Pearson Correlation	1	.809(**)	-.586(**)	.736(**)	.635(**)	.710(**)	.879(**)	.778(**)	.827(**)
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.000	.000
	N	301	301	301	301	301	301	210	301	174
EA2	Pearson Correlation	.809(**)	1	-.501(**)	.619(**)	.571(**)	.669(**)	.760(**)	.698(**)	.796(**)
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000	.000
	N	301	301	301	301	301	301	210	301	174
REGEN	Pearson Correlation	-.586(**)	-.501(**)	1	-.521(**)	-.302(**)	-.559(**)	-.629(**)	-.662(**)	-.589(**)
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.000	.000
	N	301	301	301	301	301	301	210	301	174
RXN_LVL	Pearson Correlation	.736(**)	.619(**)	-.521(**)	1	.727(**)	.509(**)	.768(**)	.699(**)	.773(**)
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000	.000
	N	301	301	301	301	301	301	210	301	174
MAX_ LIVE_ GRPS	Pearson Correlation	.635(**)	.571(**)	-.302(**)	.727(**)	1	.317(**)	.771(**)	.614(**)	.747(**)
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000	.000
	N	301	301	301	301	301	301	210	301	174
SAM_LVL	Pearson Correlation	.710(**)	.669(**)	-.559(**)	.509(**)	.317(**)	1	.634(**)	.580(**)	.736(**)
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000	.000
	N	301	301	301	301	301	301	210	301	174
SAM_ ROE2	Pearson Correlation	.879(**)	.760(**)	-.629(**)	.768(**)	.771(**)	.634(**)	1	.897(**)	.929(**)
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000	.000
	N	210	210	210	210	210	210	210	210	137
REC	Pearson Correlation	.778(**)	.698(**)	-.662(**)	.699(**)	.614(**)	.580(**)	.897(**)	1	.913(**)
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000		.000
	N	301	301	301	301	301	301	210	301	174
BIG_ CROW2	Pearson Correlation	.827(**)	.796(**)	-.589(**)	.773(**)	.747(**)	.736(**)	.929(**)	.913(**)	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	
	N	174	174	174	174	174	174	137	174	174

** Correlation is significant at the 0.01 level (2-tailed).

A10. Force Ratio Pearson Correlation Test

Author's original work using SPSS 12.0.1

Correlations

		F15_ING_ ATT	RED_ING_ ATT	LOG_F15_ FLOWN_ RATIO	F15_FLOWN_ RATIO	OCA_F15_ FL	RED_TOT_ FTR_FL
F15_ING_ATT	Pearson Correlation	1	-.253(**)	-.297(**)	-.270(**)	-.180(**)	.219(**)
	Sig. (2-tailed)		.000	.000	.000	.002	.000
	N	299	299	299	299	299	299
RED_ING_ATT	Pearson Correlation	-.253(**)	1	.396(**)	.351(**)	.097	-.411(**)
	Sig. (2-tailed)	.000		.000	.000	.094	.000
	N	299	307	299	307	299	307
LOG_F15_ FLOWN_RATIO	Pearson Correlation	-.297(**)	.396(**)	1	.966(**)	.501(**)	-.773(**)
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	299	299	299	299	299	299
F15_FLOWN_ RATIO	Pearson Correlation	-.270(**)	.351(**)	.966(**)	1	.431(**)	-.644(**)
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	299	307	299	307	299	307
OCA_F15_FL	Pearson Correlation	-.180(**)	.097	.501(**)	.431(**)	1	.103
	Sig. (2-tailed)	.002	.094	.000	.000		.077
	N	299	299	299	299	299	299
RED_TOT_ FTR_FL	Pearson Correlation	.219(**)	-.411(**)	-.773(**)	-.644(**)	.103	1
	Sig. (2-tailed)	.000	.000	.000	.000	.077	
	N	299	307	299	307	299	307

** Correlation is significant at the 0.01 level (2-tailed).

A11. Independent Variable Factor Analysis

Author's original work using SPSS 12.0.1

Communalities

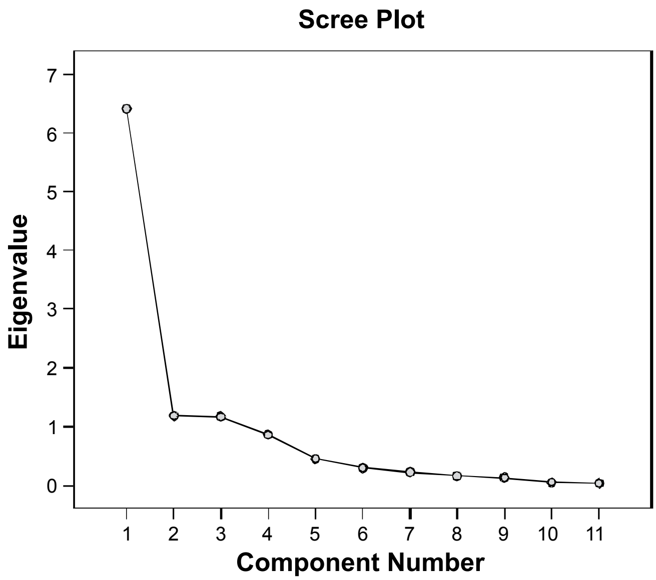
	Initial	Extraction
LOG_F15_FLOWN_RATIO	1.000	.952
THRT_AC2	1.000	.848
WEAPON2	1.000	.859
TACTIC2	1.000	.812
EA2	1.000	.791
RXN_LVL	1.000	.808
MAX_LIVE_GRPS	1.000	.784
SAM_ROE2	1.000	.932
REC	1.000	.911
BIG_CROW2	1.000	.935
LIGHT	1.000	.992

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.407	58.241	58.241	6.407	58.241	58.241	5.679	51.627	51.627
2	1.188	10.797	69.038	1.188	10.797	69.038	1.860	16.913	68.540
3	1.170	10.639	79.676	1.170	10.639	79.676	1.069	9.718	78.258
4	.860	7.814	87.491	.860	7.814	87.491	1.016	9.232	87.491
5	.454	4.132	91.622						
6	.302	2.741	94.363						
7	.226	2.052	96.415						
8	.166	1.508	97.923						
9	.134	1.216	99.139						
10	.056	.508	99.647						
11	.039	.353	100.000						

Extraction Method: Principal Component Analysis.



Component Matrix (a)

	Component			
	1	2	3	4
LOG_F15_FLOWN_RATIO	.072	.586	.587	-.509
THRT_AC2	.650	-.413	.454	.222
WEAPON2	.516	-.353	.673	.123
TACTIC2	.899	.042	-.025	-.028
EA2	.844	.139	.021	-.242
RXN_LVL	.845	.212	-.219	-.024
MAX_LIVE_GRPS	.857	.022	-.187	.120
SAM_ROE2	.959	.032	-.102	.024
REC	.941	.055	-.148	.016
BIG_CROW2	.962	.047	-.078	.010
LIGHT	-.105	.690	.209	.679

Extraction Method: Principal Component Analysis.
a 4 components extracted.

Rotated Component Matrix (a)

	Component			
	1	2	3	4
LOG_F15_FLOWN_RATIO	.028	.040	.970	.092
THRT_AC2	.369	.839	-.084	-.042
WEAPON2	.194	.896	.129	-.032
TACTIC2	.852	.284	.060	-.046
EA2	.815	.194	.267	-.134
RXN_LVL	.896	.037	.041	.031
MAX_LIVE_GRPS	.853	.196	-.134	.025
SAM_ROE2	.927	.267	-.018	-.031
REC	.930	.213	-.028	-.030
BIG_CROW2	.926	.275	.012	-.027
LIGHT	-.041	-.051	.089	.990

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 5 iterations.

Component Transformation Matrix

Component	1	2	3	4
1	.928	.367	.037	-.052
2	.209	-.497	.559	.630
3	-.306	.743	.565	.186
4	-.036	.258	-.606	.752

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Component Score Coefficient Matrix

	Component			
	1	2	3	4
LOG_F15_FLOWN_RATIO	-.019	-.021	.918	-.042
THRT_AC2	-.107	.565	-.128	.042
WEAPON2	-.169	.641	.076	.023
TACTIC2	.145	.010	.033	-.014
EA2	.151	-.069	.251	-.141
RXN_LVL	.218	-.186	.016	.050
MAX_LIVE_GRPS	.172	-.042	-.159	.080
SAM_ROE2	.170	-.016	-.045	.014
REC	.184	-.058	-.051	.012
BIG_CROW2	.168	-.011	-.017	.013
LIGHT	.023	.042	-.053	.994

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. Component Scores.

Component Score Covariance Matrix

Component	1	2	3	4
1	1.000	.000	.000	.000
2	.000	1.000	.000	.000
3	.000	.000	1.000	.000
4	.000	.000	.000	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. Component Scores.

A12. Final Data Set Testing

Author's original work using SPSS 12.0.1

Correlations

		LOG_F15_FLOWN_RATIO	F15_ING_ATT	RED_ING_ATT	LIGHT	THRT_AC2	WEAP-ON2	TAC-TIC2	EA2	REGEN2	RXN_LVL	MAX_LIVE_GRPS	SAM_LVL	SAM_ROE2	REC	BIG_CROW2
LOG_F15_FLOWN_RATIO	Pearson Correlation	1	-.304 (**)	.368 (**)	.214 (**)	.031	.031	-.012	.047	-.046	-.006	-.083	.025	-.022	-.041	.014
	Sig. (2-tailed)		.000	.000	.001	.631	.631	.854	.473	.479	.924	.201	.702	.794	.524	.859
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
F15_ING_ATT	Pearson Correlation	-.304 (**)	1	-.241 (**)	-.095	.214 (**)	.214 (**)	.152 (*)	.098	.113	.112	.102	.134 (*)	.171 (*)	.177 (**)	.064
	Sig. (2-tailed)	.000		.000	.144	.001	.001	.019	.132	.082	.084	.116	.038	.037	.006	.400
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
RED_ING_ATT	Pearson Correlation	.368 (**)	-.241 (**)	1	.122	.013	.013	.044	.087	.015	-.035	-.078	.017	.074	.011	.093
	Sig. (2-tailed)	.000	.000		.061	.844	.844	.501	.182	.816	.592	.227	.799	.369	.870	.223
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
LIGHT	Pearson Correlation	.214 (**)	-.095	.122	1	-.118	-.118	-.101	-.090	.046	-.023	-.040	-.053	-.057	-.078	-.070
	Sig. (2-tailed)	.001	.144	.061		.069	.069	.120	.164	.476	.723	.542	.411	.491	.227	.356
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
THRT_AC2	Pearson Correlation	.031	.214 (**)	.013	-.118	1	1.000 (**)	.506 (**)	.358 (**)	.307 (**)	.343 (**)	.346 (**)	.517 (**)	.531 (**)	.521 (**)	.579 (**)
	Sig. (2-tailed)	.631	.001	.844	.069		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000

Correlations (continued)

		LOG_F15_FLOWN_RATIO	F15_ING_ATT	RED_ING_ATT	LIGHT	THRT_AC2	WEAP-ON2	TAC-TIC2	EA2	REGEN2	RXN_LVL	MAX_LIVE_GRPS	SAM_LVL	SAM_ROE2	REC	BIG_CROW2
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
WEAP-ON2	Pearson Correlation	.031	.214 (**)	.013	-.118	1.000 (**)	1	.506 (**)	.358 (**)	.307 (**)	.343 (**)	.346 (**)	.517 (**)	.531 (**)	.521 (**)	.579 (**)
	Sig. (2-tailed)	.631	.001	.844	.069	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
TACTIC2	Pearson Correlation	-.012	.152(*)	.044	-.101	.506 (**)	.506 (**)	1	.807 (**)	.537 (**)	.728 (**)	.668 (**)	.771 (**)	.915 (**)	.821 (**)	.827 (**)
	Sig. (2-tailed)	.854	.019	.501	.120	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
EA2	Pearson Correlation	.047	.098	.087	-.090	.358 (**)	.358 (**)	.807 (**)	1	.441 (**)	.633 (**)	.621 (**)	.629 (**)	.820 (**)	.740 (**)	.796 (**)
	Sig. (2-tailed)	.473	.132	.182	.164	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
REGEN2	Pearson Correlation	-.046	.113	.015	.046	.307 (**)	.307 (**)	.537 (**)	.441 (**)	1	.490 (**)	.314 (**)	.544 (**)	.623 (**)	.656 (**)	.589 (**)
	Sig. (2-tailed)	.479	.082	.816	.476	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
RXN_LVL	Pearson Correlation	-.006	.112	-.035	-.023	.343 (**)	.343 (**)	.728 (**)	.633 (**)	.490 (**)	1	.763 (**)	.593 (**)	.793 (**)	.707 (**)	.773 (**)
	Sig. (2-tailed)	.924	.084	.592	.723	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
MAX_LIVE_GRPS	Pearson Correlation	-.083	.102	-.078	-.040	.346 (**)	.346 (**)	.668 (**)	.621 (**)	.314 (**)	.76 (**)	1	.416 (**)	.812 (**)	.640 (**)	.747 (**)

Correlations (continued)

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP-ON2	TAC-TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
	Sig. (2-tailed)	.201	.116	.227	.542	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
SAM_ LVL	Pearson Correlation	.025	.134(*)	.017	-.053	.517 (**)	.517 (**)	.771 (**)	.629 (**)	.544 (**)	.593 (**)	.416 (**)	1	.852 (**)	.747 (**)	.736 (**)
	Sig. (2-tailed)	.702	.038	.799	.411	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
SAM_ ROE2	Pearson Correlation	-.022	.171(*)	.074	-.057	.531 (**)	.531 (**)	.915 (**)	.820 (**)	.623 (**)	.793 (**)	.812 (**)	.852 (**)	1	.951 (**)	.929 (**)
	Sig. (2-tailed)	.794	.037	.369	.491	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000
	N	148	148	148	148	148	148	148	148	148	148	148	148	148	148	137
REC	Pearson Correlation	-.041	.177 (**)	.011	-.078	.521 (**)	.521 (**)	.821 (**)	.740 (**)	.656 (**)	.707 (**)	.640 (**)	.747 (**)	.951 (**)	1	.913 (**)
	Sig. (2-tailed)	.524	.006	.870	.227	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000
	N	239	239	239	239	239	239	239	239	239	239	239	239	148	239	174
BIG_ CROW2	Pearson Correlation	.014	.064	.093	-.070	.579 (**)	.579 (**)	.827 (**)	.796 (**)	.589 (**)	.773 (**)	.747 (**)	.736 (**)	.929 (**)	.913 (**)	1
	Sig. (2-tailed)	.859	.400	.223	.356	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	
	N	174	174	174	174	174	174	174	174	174	174	174	174	137	174	174

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

T-test

Group Statistics

	WEAPON2	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	SHORT	171	.108906	.1434054	.0109665
	LONG	67	.186343	.1803651	.0220351
RED_ING_ATT	SHORT	172	.726205	.2266806	.0172842
	LONG	74	.733235	.2310861	.0268632

Independent Samples Test

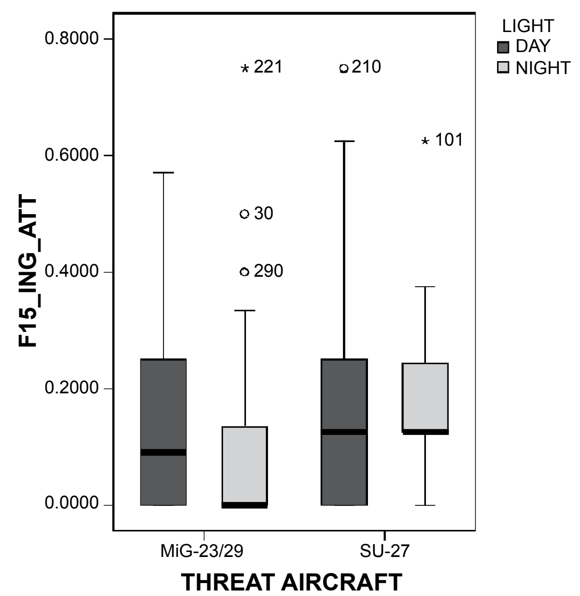
		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	3.940	.048	-3.475	236	.001	-.0774374	.0222873	-.1213449	-.0335298
	Equal variances not assumed			-3.146	100.354	.002	-.0774374	.0246132	-.1262671	-.0286076
RED_ING_ATT	Equal variances assumed	.078	.780	-.222	244	.825	-.0070307	.0316984	-.0694680	.0554066
	Equal variances not assumed			-.220	136.002	.826	-.0070307	.0319433	-.0702006	.0561392

THRT_AC2*LIGHT

Case Processing Summary

	THRT_AC2	LIGHT	Cases					
			Valid		Missing		Total	
			N	Percent	N	Percent	N	Percent
F15_ING_ATT	MiG-23/29	DAY	99	100.0%	0	.0%	99	100.0%
		NIGHT	72	100.0%	0	.0%	72	100.0%
	SU-27	DAY	48	100.0%	0	.0%	48	100.0%
		NIGHT	20	100.0%	0	.0%	20	100.0%

F15_ING_ATT

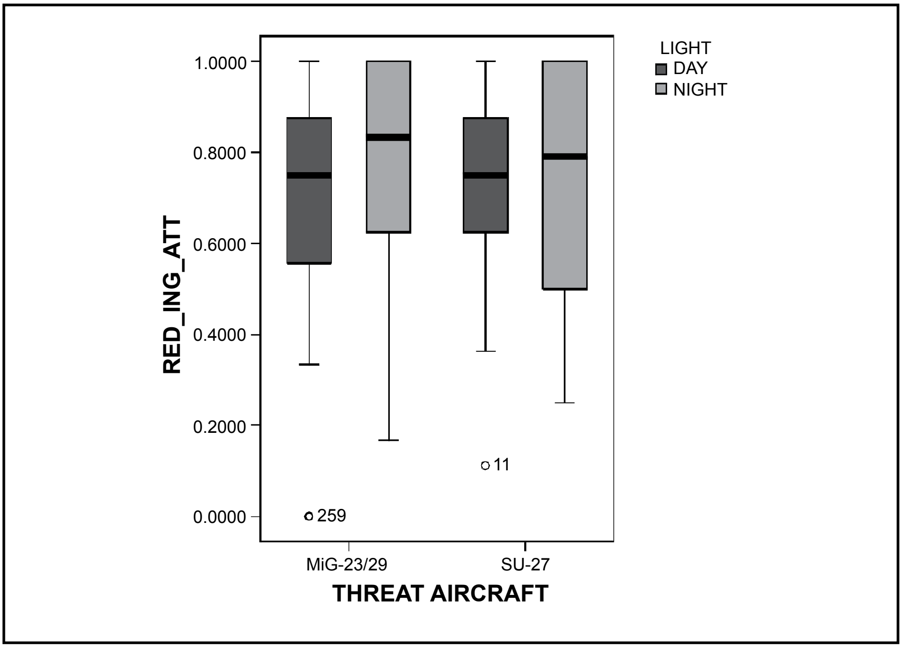


THRT_AC2*LIGHT

Case Processing Summary

	THRT_AC2	LIGHT	Cases					
			Valid		Missing		Total	
			N	Percent	N	Percent	N	Percent
RED_ING_ATT	MiG-23/29	DAY	99	100.0%	0	.0%	99	100.0%
		NIGHT	72	100.0%	0	.0%	72	100.0%
	SU-27	DAY	48	100.0%	0	.0%	48	100.0%
		NIGHT	20	100.0%	0	.0%	20	100.0%

RED_ING_ATT



DAY-NIGHT T-test N=239

Group Statistics

	LIGHT	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	DAY	147	.141996	.1647666	.0135897
	NIGHT	92	.111244	.1456968	.0151899
RED_ING_ATT	DAY	147	.711131	.2143393	.0176784
	NIGHT	92	.765910	.2253483	.0234942

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	T	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	3.347	.069	1.467	237	.144	.0307522	.0209665	-.0105523	.0720567
	Equal variances not assumed			1.509	210.799	.133	.0307522	.0203817	-.0094259	.0709303
RED_ING_ATT	Equal variances assumed	.649	.421	-1.885	237	.061	-.0547795	.0290643	-.1120369	.0024779
	Equal variances not assumed			-1.863	186.046	.064	-.0547795	.0294024	-.1127845	.0032255

DAY-NIGHT T-test Short MiG-23/29 N=171

Group Statistics

	LIGHT	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	DAY	99	.121074	.1472703	.0148012
	NIGHT	72	.092175	.1371633	.0161648
RED_ING_ATT	DAY	99	.698647	.2210243	.0222138
	NIGHT	72	.774182	.2133213	.0251402

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.528	.218	1.304	169	.194	.0288997	.0221660	-.0148583	.0726576
	Equal variances not assumed			1.319	158.992	.189	.0288997	.0219175	-.0143874	.0721867
RED_ING_ATT	Equal variances assumed	.083	.773	-2.239	169	.026	-.0755349	.0337376	-.1421363	-.0089334
	Equal variances not assumed			-2.252	156.175	.026	-.0755349	.0335482	-.1418016	-.0092682

DAY-NIGHT T-test Long SU-27 N=68

Group Statistics

	LIGHT	N	Mean	Std. Deviation	Std. Error Mean
F15_ING_ATT	DAY	48	.185148	.1904875	.0274945
	NIGHT	20	.179895	.1581954	.0353736
RED_ING_ATT	DAY	48	.736878	.1996123	.0288115
	NIGHT	20	.736131	.2682850	.0599903

Independent Samples Test

		Levene's Test for Equality of Variances		T-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
F15_ING_ATT	Equal variances assumed	1.332	.253	.109	66	.914	.0052536	.0483800	-.0913401	.1018473
	Equal variances not assumed			.117	42.606	.907	.0052536	.0448022	-.0851228	.0956300
RED_ING_ATT	Equal variances assumed	5.214	.026	.013	66	.990	.0007468	.0589709	-.1169925	.1184860
	Equal variances not assumed			.011	28.170	.991	.0007468	.0665503	-.1355384	.1370319

Correlations Short MiG-23/29 N=171

Correlations

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP-ON2	TAC-TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
LOG_ F15_ FLOWN_ RATIO	Pearson Correlation	1	-.366 (**)	.386 (**)	.196 (*)	.(a)	.(a)	.003	.040	-.101	-.008	-.081	.012	-.016	-.065	-.001
	Sig. (2-tailed)		.000	.000	.010	.	.	.971	.606	.188	.915	.291	.880	.872	.399	.989
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
F15_ ING_ ATT	Pearson Correlation	-.366 (**)	1	-.304 (**)	-.100	.(a)	.(a)	.031	.041	.058	.026	-.004	.036	.073	.074	-.081
	Sig. (2-tailed)	.000		.000	.194	.	.	.686	.592	.447	.740	.960	.640	.450	.339	.374
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
RED_ ING_ ATT	Pearson Correlation	.386 (**)	-.304 (**)	1	.170 (*)	.(a)	.(a)	.019	.008	.036	.018	-.030	.014	.105	.043	.127
	Sig. (2-tailed)	.000	.000		.026	.	.	.808	.915	.641	.816	.699	.859	.277	.575	.161
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
LIGHT	Pearson Correlation	.196(*)	-.100	.170(*)	1	.(a)	.(a)	.003	-.016	.077	-.006	-.016	.010	-.001	-.016	.008
	Sig. (2-tailed)	.010	.194	.026		.	.	.970	.836	.320	.939	.840	.896	.991	.833	.929
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
THRT_ AC2	Pearson Correlation	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)
	Sig. (2-tailed)	.	.	.	.		.	.	.	.	.	.	.	.	.	.

Correlations (continued)

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP- ON2	TAC- TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
WEAP- ON2	Pearson Correlation	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)
	Sig. (2-tailed)	.	.	.	.	.		.	.	.	.	.	.	.	.	.
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
TACTIC2	Pearson Correlation	.003	.031	.019	.003	.(a)	.(a)	1	.759 (**)	.536 (**)	.726 (**)	.644 (**)	.801 (**)	.910 (**)	.790 (**)	.778 (**)
	Sig. (2-tailed)	.971	.686	.808	.970	.	.		.000	.000	.000	.000	.000	.000	.000	.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
EA2	Pearson Correlation	.040	.041	.008	-.016	.(a)	.(a)	.759 (**)	1	.449 (**)	.610 (**)	.582 (**)	.660 (**)	.775 (**)	.762 (**)	.787 (**)
	Sig. (2-tailed)	.606	.592	.915	.836	.	.	.000		.000	.000	.000	.000	.000	.000	.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
REGEN2	Pearson Correlation	-.101	.058	.036	.077	.(a)	.(a)	.536 (**)	.449 (**)	1	.418 (**)	.274 (**)	.495 (**)	.589 (**)	.648 (**)	.549 (**)
	Sig. (2-tailed)	.188	.447	.641	.320	.	.	.000	.000		.000	.000	.000	.000	.000	.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
RXN_ LVL	Pearson Correlation	-.008	.026	.018	-.006	.(a)	.(a)	.726 (**)	.610 (**)	.418 (**)	1	.655 (**)	.600 (**)	.768 (**)	.670 (**)	.775 (**)
	Sig. (2-tailed)	.915	.740	.816	.939	.	.	.000	.000	.000		.000	.000	.000	.000	.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
MAX_ LIVE_ GRPS	Pearson Correlation	-.081	-.004	-.030	-.016	.(a)	.(a)	.644 (**)	.582 (**)	.274 (**)	.655 (**)	1	.412 (**)	.749 (**)	.623 (**)	.759 (**)

Correlations (continued)

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP-ON2	TAC-TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
	Sig. (2-tailed)	.291	.960	.699	.840	.	.	.000	.000	.000	.000		.000	.000	.000	.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
SAM_ LVL	Pearson Correlation	.012	.036	.014	.010	.(a)	.(a)	.801 (**)	.660 (**)	.495 (**)	.600 (**)	.412 (**)	1	.866 (**)	.711 (**)	.689 (**)
	Sig. (2-tailed)	.880	.640	.859	.896	.	.	.000	.000	.000	.000	.000		.000	.000	.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
SAM_ ROE2	Pearson Correlation	-.016	.073	.105	-.001	.(a)	.(a)	.910 (**)	.775 (**)	.589 (**)	.768 (**)	.749 (**)	.866 (**)	1	.924 (**)	.886 (**)
	Sig. (2-tailed)	.872	.450	.277	.991	.	.	.000	.000	.000	.000	.000	.000		.000	.000
	N	110	110	110	110	110	110	110	110	110	110	110	110	110	110	100
REC	Pearson Correlation	-.065	.074	.043	-.016	.(a)	.(a)	.790 (**)	.762 (**)	.648 (**)	.670 (**)	.623 (**)	.711 (**)	.924 (**)	1	.857 (**)
	Sig. (2-tailed)	.399	.339	.575	.833	.	.	.000	.000	.000	.000	.000	.000	.000		.000
	N	171	171	171	171	171	171	171	171	171	171	171	171	110	171	123
BIG_ CROW2	Pearson Correlation	-.001	-.081	.127	.008	.(a)	.(a)	.778 (**)	.787 (**)	.549 (**)	.775 (**)	.759 (**)	.689 (**)	.886 (**)	.857 (**)	1
	Sig. (2-tailed)	.989	.374	.161	.929	.	.	.000	.000	.000	.000	.000	.000	.000	.000	
	N	123	123	123	123	123	123	123	123	123	123	123	123	100	123	123

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
a Cannot be computed because at least one of the variables is constant.

Correlations Long SU-27 N=68

Correlations

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP-ON2	TAC-TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
LOG_ F15_ FLOWN_ RATIO	Pearson Correlation	1	-.223	.316 (**)	.292 (*)	.(a)	.(a)	-.141	.033	.185	-.048	-.146	.(a)	-.140	-.081	-.165
	Sig. (2-tailed)		.068	.009	.016	.	.	.252	.788	.132	.695	.236	.	.401	.514	.248
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
F15_ ING_ ATT	Pearson Correlation	-.223	1	-.144	-.013	.(a)	.(a)	.098	-.012	.038	.079	.076	.(a)	.130	.104	.145
	Sig. (2-tailed)	.068		.242	.914	.	.	.429	.922	.757	.524	.539	.	.436	.397	.312
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
RED_ ING_ ATT	Pearson Correlation	.316 (**)	-.144	1	-.002	.(a)	.(a)	.110	.286 (*)	-.111	-.202	-.190	.(a)	-.240	-.139	-.186
	Sig. (2-tailed)	.009	.242		.990	.	.	.371	.018	.369	.098	.121	.	.147	.260	.190
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
LIGHT	Pearson Correlation	.292(*)	-.013	-.002	1	.(a)	.(a)	-.198	-.149	.161	.090	.031	.(a)	.006	-.037	-.071
	Sig. (2-tailed)	.016	.914	.990		.	.	.106	.226	.189	.466	.804	.	.970	.767	.619
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
THRT_ AC2	Pearson Correlation	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)
	Sig. (2-tailed)	.	.	.	.		.	.	.	.	.	.	.	.	.	.

Correlations (continued)

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP- ON2	TAC- TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
WEAP- ON2	Pearson Correlation	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)
	Sig. (2-tailed)	.	.	.	.	.		.	.	.	.	.	.	.	.	.
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
TACTIC2	Pearson Correlation	-.141	.098	.110	-.198	.(a)	.(a)	1	.828 (**)	.161	.562 (**)	.595 (**)	.(a)	.725 (**)	.656 (**)	.719 (**)
	Sig. (2-tailed)	.252	.429	.371	.106	.	.		.000	.190	.000	.000	.	.000	.000	.000
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
EA2	Pearson Correlation	.033	-.012	.286(*)	-.149	.(a)	.(a)	.828 (**)	1	.076	.509 (**)	.573 (**)	.(a)	.651 (**)	.489 (**)	.674 (**)
	Sig. (2-tailed)	.788	.922	.018	.226	.	.	.000		.537	.000	.000	.	.000	.000	.000
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
REGEN2	Pearson Correlation	.185	.038	-.111	.161	.(a)	.(a)	.161	.076	1	.578 (**)	.216	.(a)	.449 (**)	.361 (**)	.379 (**)
	Sig. (2-tailed)	.132	.757	.369	.189	.	.	.190	.537		.000	.077	.	.005	.002	.006
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
RXN_ LVL	Pearson Correlation	-.048	.079	-.202	.090	.(a)	.(a)	.562 (**)	.509 (**)	.578 (**)	1	.922 (**)	.(a)	.884 (**)	.642 (**)	.739 (**)
	Sig. (2-tailed)	.695	.524	.098	.466	.	.	.000	.000	.000		.000	.	.000	.000	.000
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
MAX_ LIVE_ GRPS	Pearson Correlation	-.146	.076	-.190	.031	.(a)	.(a)	.595 (**)	.573 (**)	.216	.922 (**)	1	.(a)	.946 (**)	.596 (**)	.726 (**)

Correlations (continued)

		LOG_ F15_ FLOWN_ RATIO	F15_ ING_ ATT	RED_ ING_ ATT	LIGHT	THRT_ AC2	WEAP- ON2	TAC- TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
	Sig. (2-tailed)	.236	.539	.121	.804	.	.	.000	.000	.077	.000		.	.000	.000	.000
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
SAM_ LVL	Pearson Correlation	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)	.(a)
	Sig. (2-tailed)	.	.	.	.	.	.	.	.	.	.	.		.	.	.
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
SAM_ ROE2	Pearson Correlation	-.140	.130	-.240	.006	.(a)	.(a)	.725 (**)	.651 (**)	.449 (**)	.884 (**)	.946 (**)	.(a)	1	1.000 (**)	1.000 (**)
	Sig. (2-tailed)	.401	.436	.147	.970	.	.	.000	.000	.005	.000	.000	.		.000	.000
	N	38	38	38	38	38	38	38	38	38	38	38	38	38	38	37
REC	Pearson Correlation	-.081	.104	-.139	-.037	.(a)	.(a)	.656 (**)	.489 (**)	.361 (**)	.642 (**)	.596 (**)	.(a)	1.000 (**)	1	1.000 (**)
	Sig. (2-tailed)	.514	.397	.260	.767	.	.	.000	.000	.002	.000	.000	.	.000		.000
	N	68	68	68	68	68	68	68	68	68	68	68	68	38	68	51
BIG_ CROW2	Pearson Correlation	-.165	.145	-.186	-.071	.(a)	.(a)	.719 (**)	.674 (**)	.379 (**)	.739 (**)	.726 (**)	.(a)	1.000 (**)	1.000 (**)	1
	Sig. (2-tailed)	.248	.312	.190	.619	.	.	.000	.000	.006	.000	.000	.	.000	.000	
	N	51	51	51	51	51	51	51	51	51	51	51	51	37	51	51

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).
a Cannot be computed because at least one of the variables is constant.

Appendix B

Regression Analysis

B1. MiG-23/29 Short Air-to-Air Missile Regression Lines

Author's original work using SPSS 12.0.1

Variables Entered/Removed (b)

Model	Variables Entered	Variables Removed	Method
1	LOG_F15_FLOWN_RATIO(a)	.	Enter

a All requested variables entered.
b Dependent Variable: F15_ING_ATT

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.366(a)	.134	.129	.1338707

a Predictors: (Constant), LOG_F15_FLOWN_RATIO

ANOVA (b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.467	1	.467	26.078	.000(a)
	Residual	3.029	169	.018		
	Total	3.496	170			

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: F15_ING_ATT

Coefficients (a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Toler-ance	VIF
1	(Constant)	.123	.011		11.599	.000					
	LOG_F15_FLOWN_RATIO	-.137	.027	-.366	-5.107	.000	-.366	-.366	-.366	1.000	1.000

a Dependent Variable: F15_ING_ATT

Collinearity Diagnostics (a)

Model	Dimension	Eigen value	Condition Index	Variance Proportions	
				(Constant)	LOG_F15_FLOWN_RATIO
1	1	1.260	1.000	.37	.37
	2	.740	1.304	.63	.63

a Dependent Variable: F15_ING_ATT

Regression MiG Short

Variables Entered/Removed (b)

Model	Variables Entered	Variables Removed	Method
1	LOG_F15_FLOWN_RATIO(a)	.	Enter

a All requested variables entered.
b Dependent Variable: RED_ING_ATT

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.386(a)	.149	.144	.2038830

a Predictors: (Constant), LOG_F15_FLOWN_RATIO

ANOVA (b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.231	1	1.231	29.618	.000(a)
	Residual	7.025	169	.042		
	Total	8.256	170			

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: RED_ING_ATT

Coefficients (a)

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Toler-ance	VIF
1	(Constant)	.708	.016		43.829	.000					
	LOG_F15_FLOWN_RATIO	.222	.041	.386	5.442	.000	.386	.386	.386	1.000	1.000

a Dependent Variable: RED_ING_ATT

Collinearity Diagnostics (a)

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	LOG_F15_FLOWN_RATIO
1	1	1.260	1.000	.37	.37
	2	.740	1.304	.63	.63

a Dependent Variable: RED_ING_ATT

B2. SU-27 Long Air-to-Air Missile Regression Lines

Author's original work using SPSS 12.0.1

Descriptive Statistics

	Mean	Std. Deviation	N
F15_ING_ATT	.183603	.1804347	68
LOG_F15_FLOWN_RATIO	.128302	.3356707	68

Correlations

		F15_ING_ATT	LOG_F15_ FLOWN_RATIO
Pearson Correlation	F15_ING_ATT	1.000	-.223
	LOG_F15_FLOWN_RATIO	-.223	1.000
Sig. (1-tailed)	F15_ING_ATT	.	.034
	LOG_F15_FLOWN_RATIO	.034	.
N	F15_ING_ATT	68	68
	LOG_F15_FLOWN_RATIO	68	68

Variables Entered/Removed (b)

Model	Variables Entered	Variables Removed	Method
1	LOG_F15_FLOWN_RATIO(a)	.	Enter

a All requested variables entered.
b Dependent Variable: F15_ING_ATT

Model Summary (b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.223(a)	.050	.035	.1772188	.050	3.454	1	66	.068

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: F15_ING_ATT

ANOVA (b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.108	1	.108	3.454	.068(a)
	Residual	2.073	66	.031		
	Total	2.181	67			

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: F15_ING_ATT

Coefficients (a)

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.199	.023		8.640	.000	.153	.245					
	LOG_F15_FLOWN_RATIO	-.120	.064	-.223	-1.858	.068	-.249	.009	-.223	-.223	-.223	1.000	1.000

a Dependent Variable: F15_ING_ATT

Collinearity Diagnostics (a)

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	LOG_F15_FLOWN_RATIO
1	1	1.359	1.000	.32	.32
	2	.641	1.457	.68	.68

a Dependent Variable: F15_ING_ATT

Casewise Diagnostics (a, b)

Case Number	Std. Residual	F15_ING_ATT
210	3.109	.750

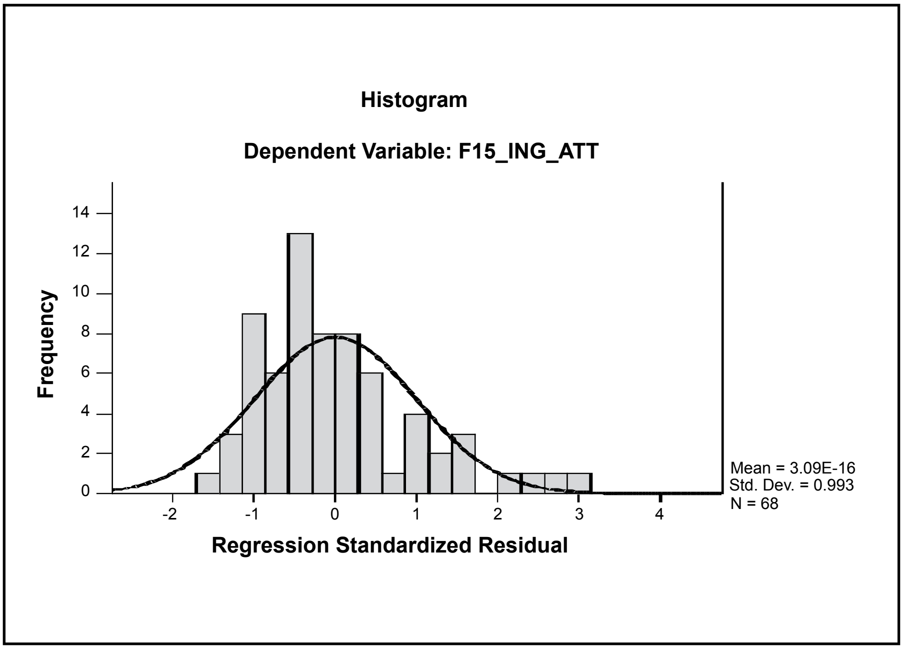
a Dependent Variable: F15_ING_ATT
b When values are missing, the substituted mean has been used in the statistical computation.

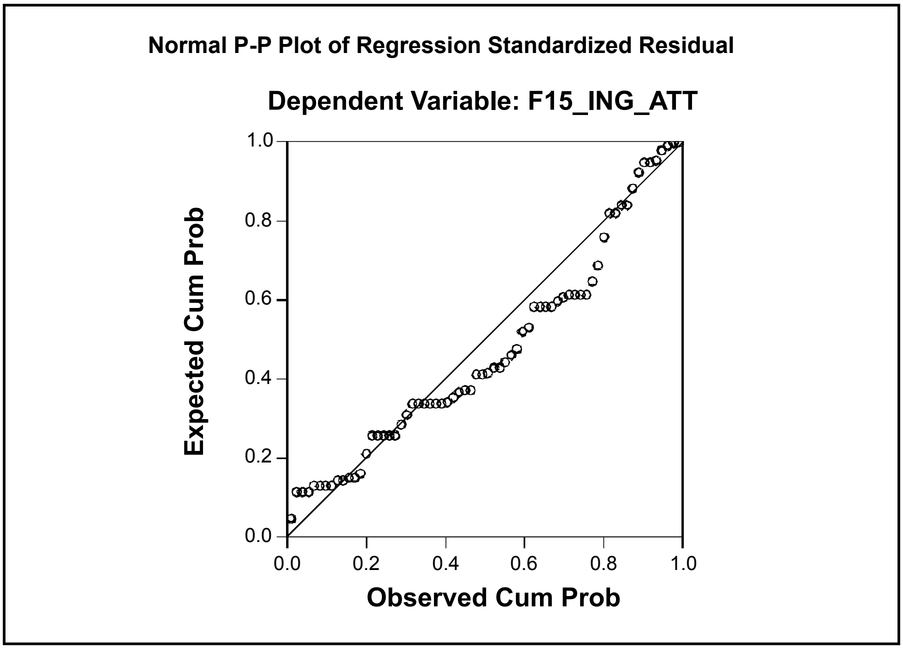
Residuals Statistics (a)

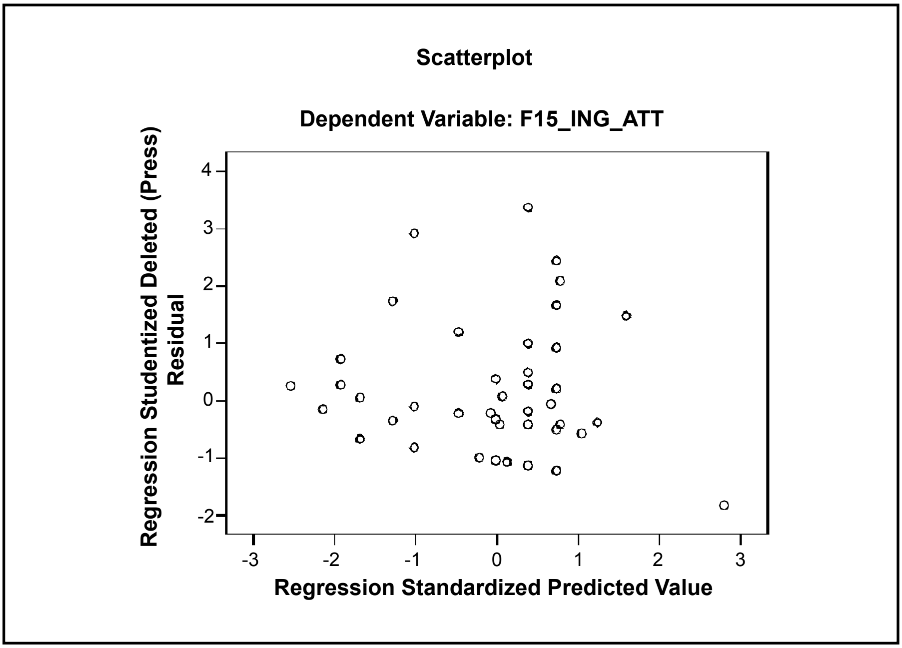
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.081413	.296186	.183603	.0402359	68
Std. Predicted Value	-2.540	2.798	.000	1.000	68
Standard Error of Predicted Value	.021	.064	.029	.009	68
Adjusted Predicted Value	.075972	.341055	.183988	.0422238	68
Residual	-.2961861	.5510176	.0000000	.1758913	68
Std. Residual	-1.671	3.109	.000	.993	68
Stud. Residual	-1.793	3.136	-.001	1.008	68
Deleted Residual	-.3410555	.5604822	-.0003847	.1813765	68
Stud. Deleted Residual	-1.825	3.373	.008	1.033	68
Mahal. Distance	.000	7.829	.985	1.532	68
Cook's Distance	.000	.244	.016	.035	68
Centered Leverage Value	.000	.117	.015	.023	68

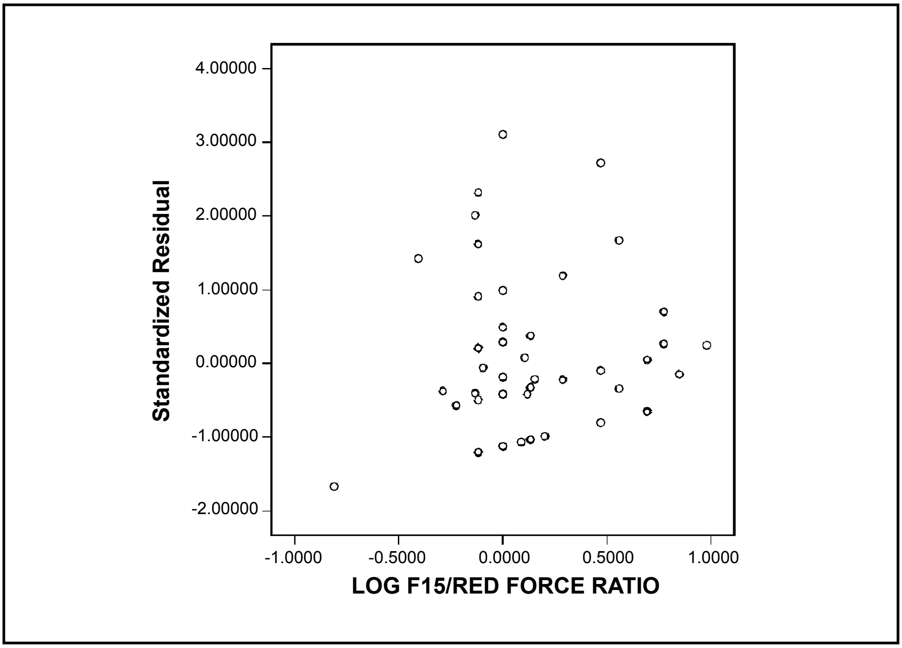
a Dependent Variable: F15_ING_ATT

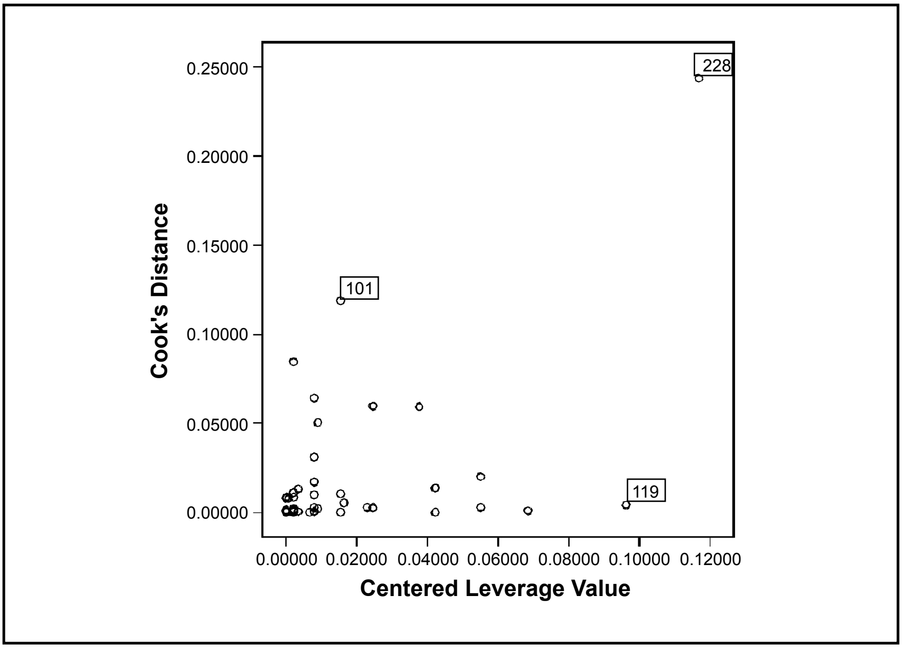
Charts




Normal P-P Plot of Regression Standardized Residual
Dependent Variable: F15_ING_ATT
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: F15_ING_ATT
Regression Studentized Deleted (Press) Residual
Regression Standardized Predicted Value
-3
-2
-1
0
1
2
3
4


4.00000
3.00000
2.00000
1.00000
0.00000
-1.00000
-2.00000
Standardized Residual
-1.0000
-0.5000
0.0000
0.5000
1.0000
LOG F15/RED FORCE RATIO


0.25000
0.20000
0.15000
0.10000
0.05000
0.00000
Cook's Distance
228
101
119
0.00000
0.02000
0.04000
0.06000
0.08000
0.10000
0.12000
Centered Leverage Value

Regression

Notes

Descriptive Statistics

	Mean	Std. Deviation	N
RED_ING_ATT	.736658	.2199147	68
LOG_F15_FLOWN_RATIO	.128302	.3356707	68

Correlations

		RED_ING_ATT	LOG_F15_ FLOWN_RATIO
Pearson Correlation	RED_ING_ATT	1.000	.316
	LOG_F15_FLOWN_RATIO	.316	1.000
Sig. (1-tailed)	RED_ING_ATT	.	.004
	LOG_F15_FLOWN_RATIO	.004	.
N	RED_ING_ATT	68	68
	LOG_F15_FLOWN_RATIO	68	68

Variables Entered/Removed (b)

Model	Variables Entered	Variables Removed	Method
1	LOG_F15_FLOWN_RATIO(a)	.	Enter

a All requested variables entered.
b Dependent Variable: RED_ING_ATT

Model Summary (b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.316(a)	.100	.086	.2102374	.100	7.310	1	66	.009

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: RED_ING_ATT

ANOVA (b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.323	1	.323	7.310	.009(a)
	Residual	2.917	66	.044		
	Total	3.240	67			

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: RED_ING_ATT

Coefficients (a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Toler-ance	VIF
1	(Constant)	.710	.027		25.993	.000	.656	.765					
	LOG_F15_FLOWN_RATIO	.207	.077	.316	2.704	.009	.054	.360	.316	.316	.316	1.000	1.000

a Dependent Variable: RED_ING_ATT

Collinearity Diagnostics (a)

Model	Dimension	Eigen value	Condition Index	Variance Proportions	
				(Constant)	LOG_F15_ FLOWN_RATIO
1	1	1.359	1.000	.32	.32
	2	.641	1.457	.68	.68

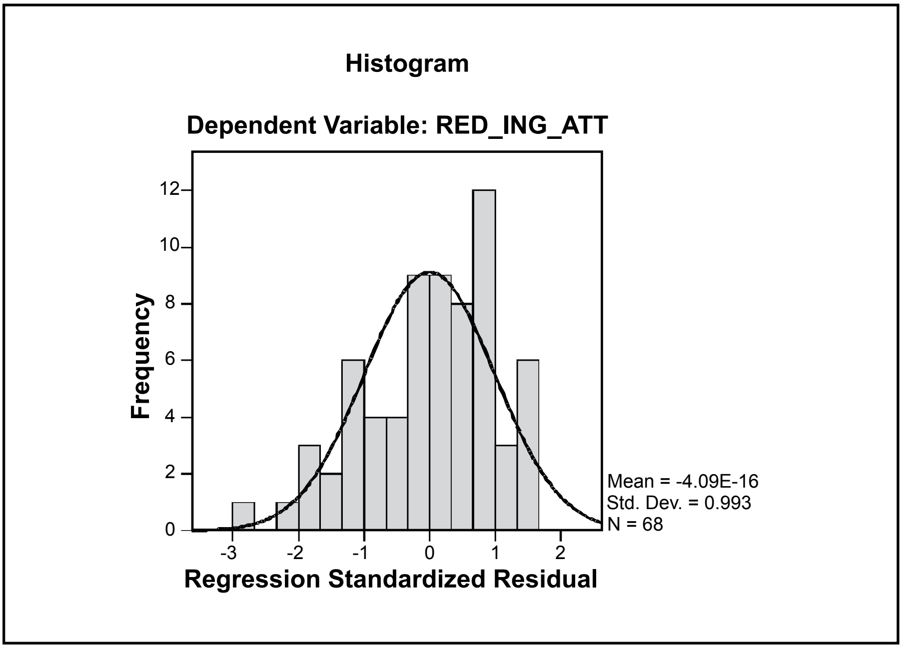
a Dependent Variable: RED_ING_ATT

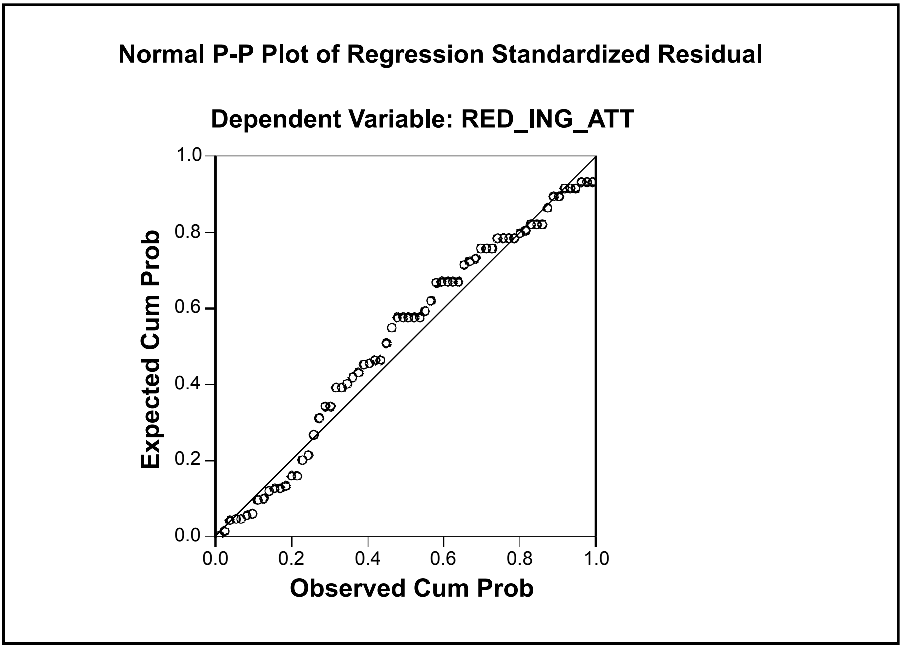
Residuals Statistics (a)

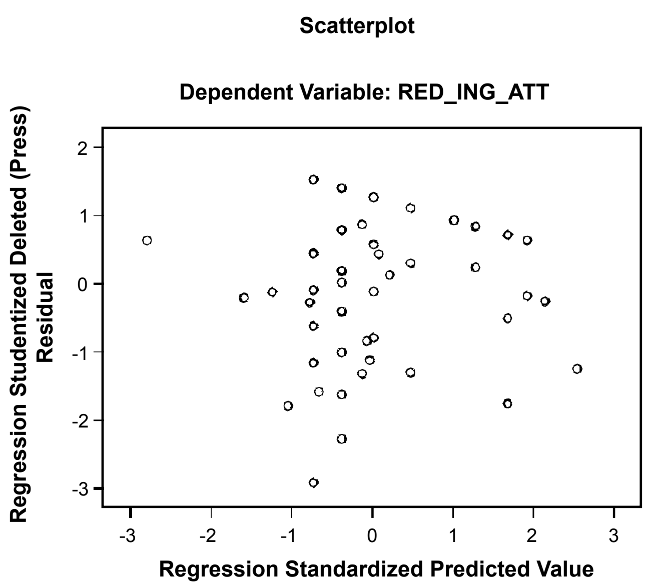
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.542350	.913029	.736658	.0694435	68
Std. Predicted Value	-2.798	2.540	.000	1.000	68
Standard Error of Predicted Value	.025	.076	.034	.011	68
Adjusted Predicted Value	.523517	.943783	.736960	.0715145	68
Residual	-.5746369	.3142520	.0000000	.2086626	68
Std. Residual	-2.733	1.495	.000	.993	68
Stud. Residual	-2.765	1.512	-.001	1.007	68
Deleted Residual	-.5880008	.3215603	-.0003016	.2146556	68
Stud. Deleted Residual	-2.918	1.527	-.005	1.020	68
Mahal. Distance	.000	7.829	.985	1.532	68
Cook's Distance	.000	.096	.014	.022	68
Centered Leverage Value	.000	.117	.015	.023	68

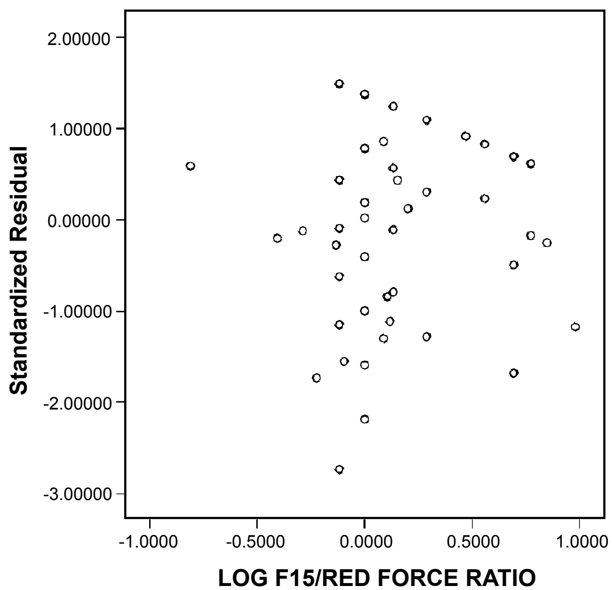
a Dependent Variable: RED_ING_ATT

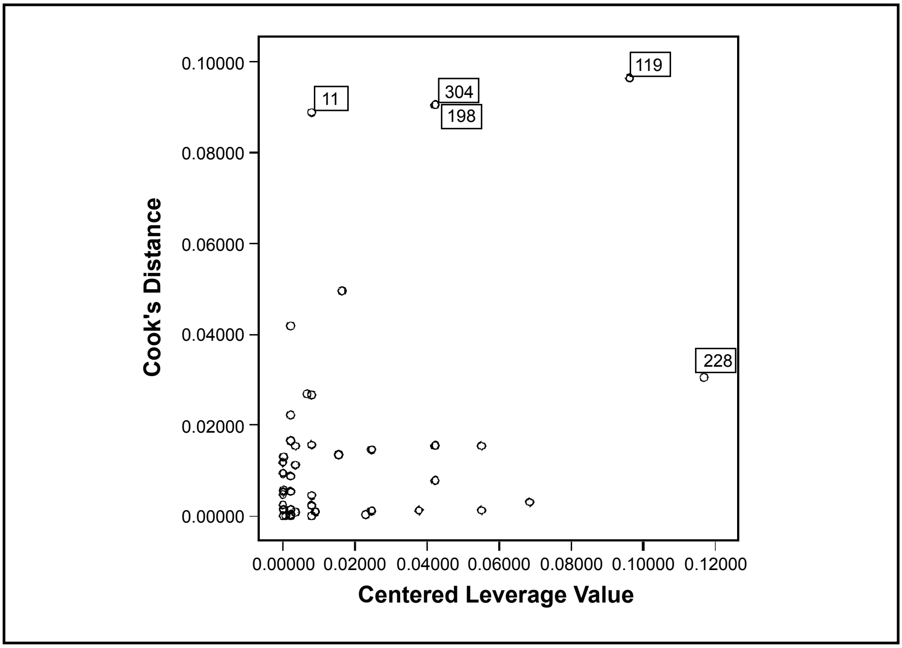
Charts


Histogram
Dependent Variable: RED_ING_ATT
Frequency
0
2
4
6
8
10
12
-3
-2
-1
0
1
2
Regression Standardized Residual
Mean = -4.09E-16
Std. Dev. = 0.993
N = 68


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: RED_ING_ATT
Expected Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0
Observed Cum Prob


Scatterplot
Dependent Variable: RED_ING_ATT
Regression Studentized Deleted (Press) Residual
2
1
0
-1
-2
-3
-3
-2
-1
0
1
2
3
Regression Standardized Predicted Value


Standardized Residual
2.00000
1.00000
0.00000
-1.00000
-2.00000
-3.00000
-1.0000
-0.5000
0.0000
0.5000
1.0000
LOG F15/RED FORCE RATIO



Cook's Distance
0.10000
0.08000
0.06000
0.04000
0.02000
0.00000
11
304
198
119
228
0.00000
0.02000
0.04000
0.06000
0.08000
0.10000
0.12000
Centered Leverage Value

Long SU-27 Regression Analysis w/o Mission #228

Warnings

For models with dependent variable F15_ING_ATT, the following variables are constants or have missing correlations: SAM_LVL. They will be deleted from the analysis.

Descriptive Statistics

	Mean	Std. Deviation	N
F15_ING_ATT	.186343	.1803651	67
LOG_F15_FLOWN_RATIO	.142321	.3175161	67
LIGHT	1.30	.461	67
TACTIC2	3.37	.599	67
EA2	3.19	.680	67
REGEN2	2.94	.239	67
RXN_LVL	2.36	.595	67
MAX_LIVE_GRPS	3.42	.497	67
SAM_LVL	2.00	.000	67
SAM_ROE2	3.62	.363	67
REC	2.67	.473	67
BIG_CROW2	3.62	.422	67

Correlations

		F15_ ING_ ATT	LOG_ F15_ FLOWN_ RATIO	LIGHT	TAC- TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
Pearson Correla- tion	F15_ ING_ATT	1.000	-.286	-.023	.115	.006	.042	.097	.095	.	.114	.116	.136
	LOG_ F15_ FLOWN_ RATIO	-.286	1.000	.283	-.104	.089	.208	-.004	-.104	.	-.069	-.055	-.120
	LIGHT	-.023	.283	1.000	-.190	-.139	.164	.101	.042	.	.015	-.030	-.053
	TACTIC2	.115	-.104	-.190	1.000	.825	.158	.554	.588	.	.448	.653	.649
	EA2	.006	.089	-.139	.825	1.000	.072	.500	.564	.	.348	.484	.557
	REGEN2	.042	.208	.164	.158	.072	1.000	.579	.214	.	.435	.360	.373
	RXN_LVL	.097	-.004	.101	.554	.500	.579	1.000	.920	.	.758	.639	.676
	MAX_ LIVE_ GRPS	.095	-.104	.042	.588	.564	.214	.920	1.000	.	.699	.592	.631
	SAM_LVL	.	.	.	.	.	.	.	.	1.000	.	.	.
	SAM_ ROE2	.114	-.069	.015	.448	.348	.435	.758	.699	.	1.000	.767	.821
	REC	.116	-.055	-.030	.653	.484	.360	.639	.592	.	.767	1.000	.893
	BIG_ CROW2	.136	-.120	-.053	.649	.557	.373	.676	.631	.	.821	.893	1.000
Sig. (1-tailed)	F15_ ING_ATT	.	.010	.425	.177	.481	.367	.219	.222	.000	.179	.174	.137
	LOG_ F15_ FLOWN_ RATIO	.010	.	.010	.200	.237	.046	.488	.200	.000	.289	.329	.167
	LIGHT	.425	.010	.	.062	.130	.092	.207	.367	.000	.453	.405	.335
	TACTIC2	.177	.200	.062	.	.000	.101	.000	.000	.000	.000	.000	.000
	EA2	.481	.237	.130	.000	.	.280	.000	.000	.000	.002	.000	.000
	REGEN2	.367	.046	.092	.101	.280	.	.000	.041	.000	.000	.001	.001
	RXN_LVL	.219	.488	.207	.000	.000	.000	.	.000	.000	.000	.000	.000
	MAX_ LIVE_ GRPS	.222	.200	.367	.000	.000	.041	.000	.	.000	.000	.000	.000
	SAM_LVL	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000
	SAM_ ROE2	.179	.289	.453	.000	.002	.000	.000	.000	.000	.	.000	.000

Correlations (continued)

		F15_ ING_ ATT	LOG_ F15_ FLOWN_ RATIO	LIGHT	TAC- TIC2	EA2	RE GE N2	RXN_ LVL	MAX_ LIVE_ GRPS	SAM_ LVL	SAM_ ROE2	REC	BIG_ CROW2
	REC	.174	.329	.405	.000	.000	.001	.000	.000	.000	.000	.	.000
	BIG_ CROW2	.137	.167	.335	.000	.000	.001	.000	.000	.000	.000	.000	.
N	F15_ ING_ATT	67	67	67	67	67	67	67	67	67	67	67	67
	LOG_ F15_ FLOWN_ RATIO	67	67	67	67	67	67	67	67	67	67	67	67
	LIGHT	67	67	67	67	67	67	67	67	67	67	67	67
	TACTIC2	67	67	67	67	67	67	67	67	67	67	67	67
	EA2	67	67	67	67	67	67	67	67	67	67	67	67
	REGEN2	67	67	67	67	67	67	67	67	67	67	67	67
	RXN_LVL	67	67	67	67	67	67	67	67	67	67	67	67
	MAX_ LIVE_ GRPS	67	67	67	67	67	67	67	67	67	67	67	67
	SAM_LVL	67	67	67	67	67	67	67	67	67	67	67	67
	SAM_ ROE2	67	67	67	67	67	67	67	67	67	67	67	67
	REC	67	67	67	67	67	67	67	67	67	67	67	67
	BIG_ CROW2	67	67	67	67	67	67	67	67	67	67	67	67

Variables Entered/Removed (a)

Model	Variables Entered	Variables Removed	Method
1	LOG_F15_ FLOWN_RATIO	.	Forward (Criterion: Probability-of-F-to-enter <= .050)

a Dependent Variable: F15_ING_ATT

Model Summary (b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.286(a)	.082	.068	.1741711	.082	5.778	1	65	.019

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: F15_ING_ATT

ANOVA (b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.175	1	.175	5.778	.019(a)
	Residual	1.972	65	.030		
	Total	2.147	66			

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: F15_ING_ATT

Coefficients (a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Toler-ance	VIF
1	(Constant)	.209	.023		8.971	.000	.163	.256					
	LOG_ F15_ FLOWN_ RATIO	-.162	.068	-.286	-2.404	.019	-.297	-.027	-.286	-.286	-.286	1.000	1.000

a Dependent Variable: F15_ING_ATT

Excluded Variables (b)

Model		Beta In	T	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	LIGHT	.062(a)	.501	.618	.062	.920	1.087	.920
	TACTIC2	.086(a)	.720	.474	.090	.989	1.011	.989
	EA2	.032(a)	.263	.793	.033	.992	1.008	.992
	REGEN2	.106(a)	.874	.385	.109	.957	1.045	.957
	RXN_LVL	.095(a)	.801	.426	.100	1.000	1.000	1.000
	MAX_LIVE_GRPS	.066(a)	.551	.584	.069	.989	1.011	.989
	SAM_ROE2	.095(a)	.792	.431	.099	.995	1.005	.995
	REC	.101(a)	.846	.401	.105	.997	1.003	.997
	BIG_CROW2	.103(a)	.858	.394	.107	.986	1.015	.986

a Predictors in the Model: (Constant), LOG_F15_FLOWN_RATIO
b Dependent Variable: F15_ING_ATT

Collinearity Diagnostics (a)

Model	Dimension	Eigen value	Condition Index	Variance Proportions	
				(Constant)	LOG_F15_FLOWN_RATIO
1	1	1.412	1.000	.29	.29
	2	.588	1.549	.71	.71

a Dependent Variable: F15_ING_ATT

Casewise Diagnostics (a, b)

Case Number	Std. Residual	F15_ING_ATT
210	3.104	.750

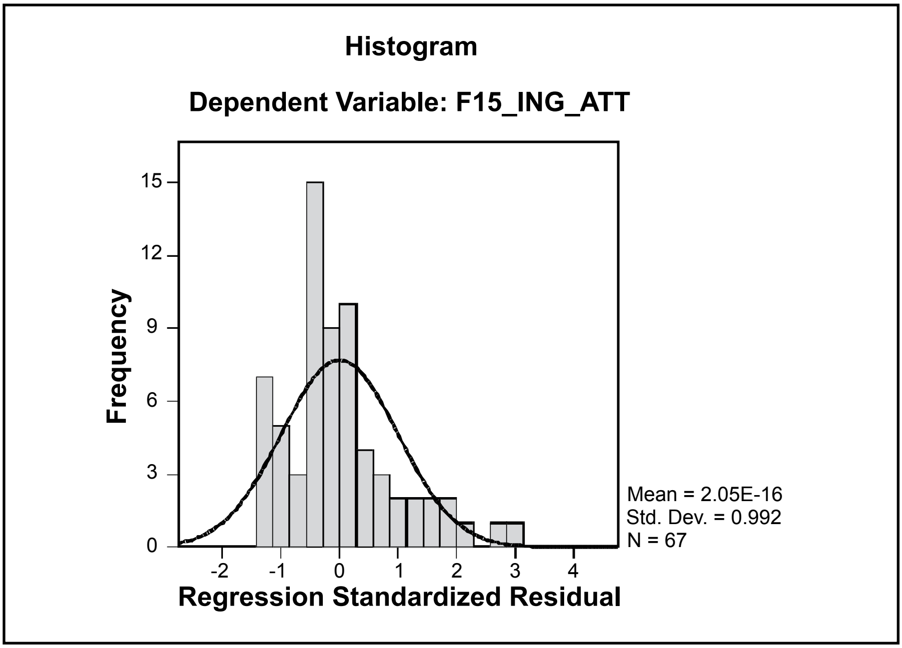
a Dependent Variable: F15_ING_ATT
b When values are missing, the substituted mean has been used in the statistical computation.

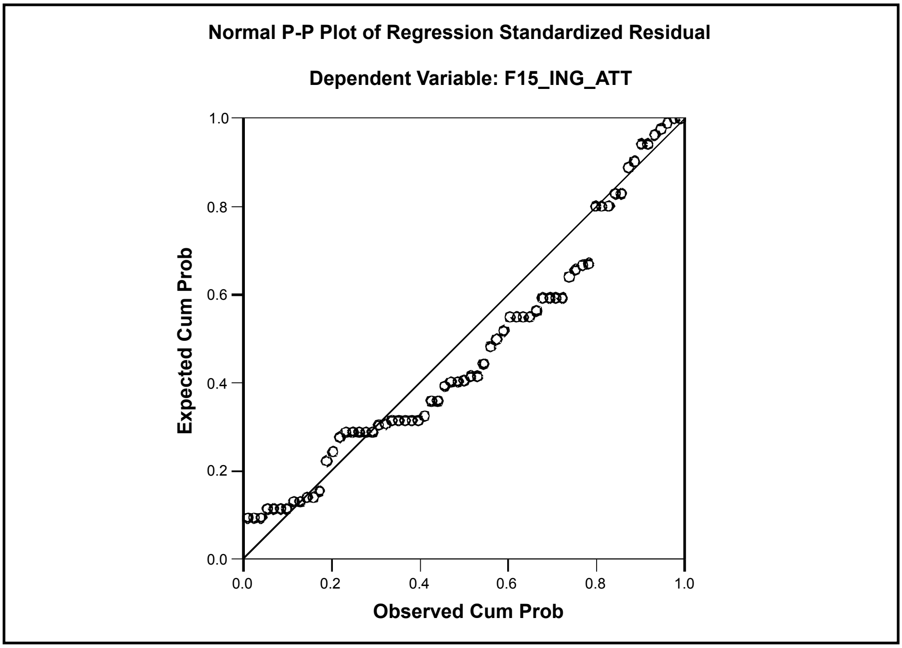
Residuals Statistics (a)

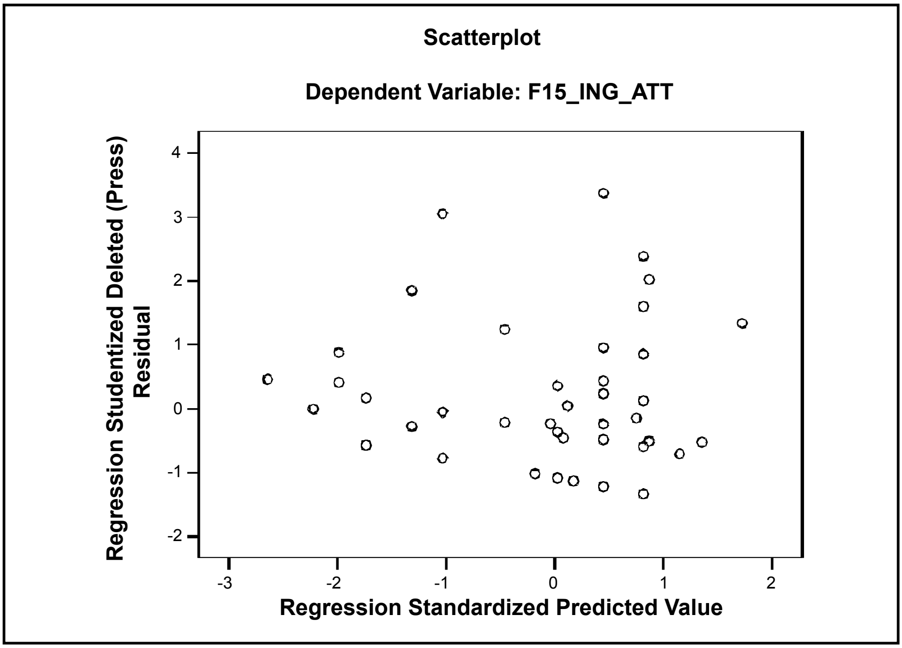
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.050254	.275249	.186343	.0515327	67
Std. Predicted Value	-2.641	1.725	.000	1.000	67
Standard Error of Predicted Value	.021	.060	.029	.009	67
Adjusted Predicted Value	.040004	.260897	.185932	.0519537	67
Residual	-.2285581	.5405580	.0000000	.1728466	67
Std. Residual	-1.312	3.104	.000	.992	67
Stud. Residual	-1.329	3.132	.001	1.006	67
Deleted Residual	-.2344409	.5504493	.0004114	.1775729	67
Stud. Deleted Residual	-1.337	3.373	.010	1.032	67
Mahal. Distance	.001	6.974	.985	1.376	67
Cook's Distance	.000	.132	.014	.023	67
Centered Leverage Value	.000	.106	.015	.021	67

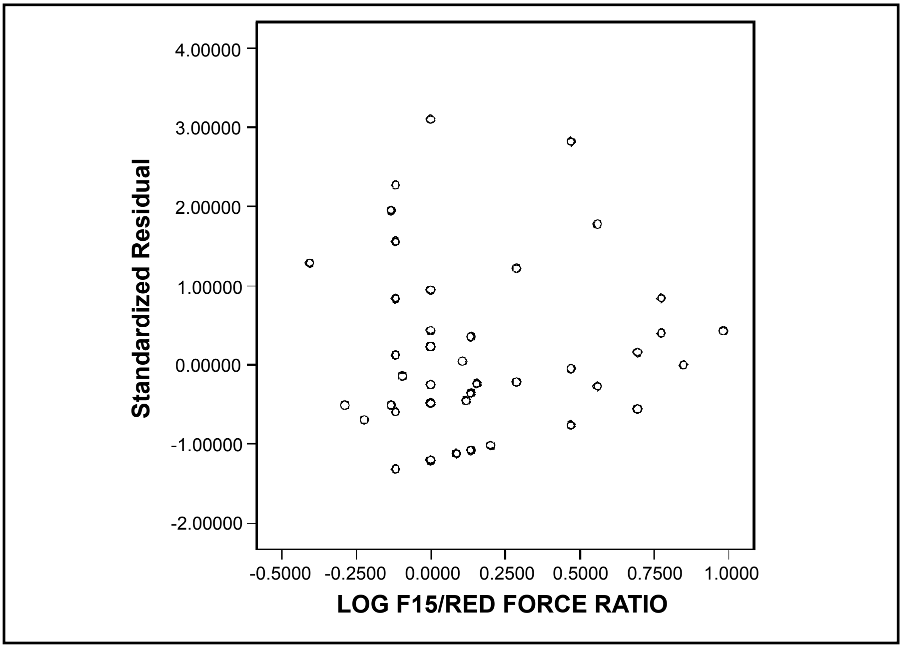
a Dependent Variable: F15_ING_ATT

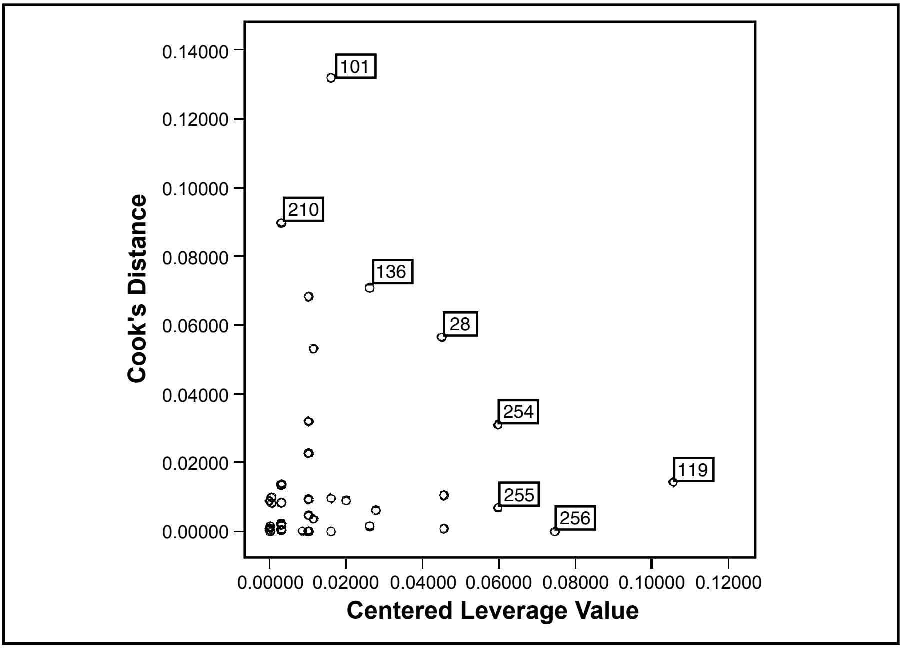
Charts




Normal P-P Plot of Regression Standardized Residual
Dependent Variable: F15_ING_ATT
Expected Cum Prob
Observed Cum Prob
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: F15_ING_ATT
Regression Studentized Deleted (Press) Residual
Regression Standardized Predicted Value
4
3
2
1
0
-1
-2
-3
-2
-1
0
1
2


4.00000
3.00000
2.00000
1.00000
0.00000
-1.00000
-2.00000
Standardized Residual
-0.5000
-0.2500
0.0000
0.2500
0.5000
0.7500
1.0000
LOG F15/RED FORCE RATIO


0.14000
0.12000
0.10000
0.08000
0.06000
0.04000
0.02000
0.00000
Cook's Distance
101
210
136
28
254
119
255
256
0.00000
0.02000
0.04000
0.06000
0.08000
0.10000
0.12000
Centered Leverage Value

Regression

Warnings

For models with dependent variable RED_ING_ATT, the following variables are constants or have missing correlations: SAM_LVL. They will be deleted from the analysis.

Descriptive Statistics

	Mean	Std. Deviation	N
RED_ING_ATT	.737703	.2214044	67
LOG_F15_FLOWN_RATIO	.142321	.3175161	67
LIGHT	1.30	.461	67
TACTIC2	3.37	.599	67
EA2	3.19	.680	67
REGEN2	2.94	.239	67
RXN_LVL	2.36	.595	67
MAX_LIVE_GRPS	3.42	.497	67
SAM_LVL	2.00	.000	67
SAM_ROE2	3.62	.363	67
REC	2.67	.473	67
BIG_CROW2	3.62	.422	67

Correlations

		RED_ING_ATT	LOG_F15_FLOWN_RATIO	LIGHT	TACTIC2	EA2	REGEN2	RXN_LVL	MAX_LIVE_GRPS	SAM_LVL	SAM_ROE2	REC	BIG_CROW2
Pearson Correlation	RED_ING_ATT	1.000	.322	-.005	.116	.295	-.110	-.199	-.186	.	-.179	-.136	-.153
	LOG_F15_FLOWN_RATIO	.322	1.000	.283	-.104	.089	.208	-.004	-.104	.	-.069	-.055	-.120
	LIGHT	-.005	.283	1.000	-.190	-.139	.164	.101	.042	.	.015	-.030	-.053
	TACTIC2	.116	-.104	-.190	1.000	.825	.158	.554	.588	.	.448	.653	.649
	EA2	.295	.089	-.139	.825	1.000	.072	.500	.564	.	.348	.484	.557
	REGEN2	-.110	.208	.164	.158	.072	1.000	.579	.214	.	.435	.360	.373
	RXN_LVL	-.199	-.004	.101	.554	.500	.579	1.000	.920	.	.758	.639	.676
	MAX_LIVE_GRPS	-.186	-.104	.042	.588	.564	.214	.920	1.000	.	.699	.592	.631
	SAM_LVL	.	.	.	.	.	.	.	.	1.000	.	.	.
	SAM_ROE2	-.179	-.069	.015	.448	.348	.435	.758	.699	.	1.000	.767	.821
	REC	-.136	-.055	-.030	.653	.484	.360	.639	.592	.	.767	1.000	.893
	BIG_CROW2	-.153	-.120	-.053	.649	.557	.373	.676	.631	.	.821	.893	1.000
Sig. (1-tailed)	RED_ING_ATT	.	.004	.485	.175	.008	.189	.053	.066	.000	.074	.137	.108
	LOG_F15_FLOWN_RATIO	.004	.	.010	.200	.237	.046	.488	.200	.000	.289	.329	.167
	LIGHT	.485	.010	.	.062	.130	.092	.207	.367	.000	.453	.405	.335
	TACTIC2	.175	.200	.062	.	.000	.101	.000	.000	.000	.000	.000	.000
	EA2	.008	.237	.130	.000	.	.280	.000	.000	.000	.002	.000	.000
	REGEN2	.189	.046	.092	.101	.280	.	.000	.041	.000	.000	.001	.001
	RXN_LVL	.053	.488	.207	.000	.000	.000	.	.000	.000	.000	.000	.000
	MAX_LIVE_GRPS	.066	.200	.367	.000	.000	.041	.000	.	.000	.000	.000	.000
	SAM_LVL	.000	.000	.000	.000	.000	.000	.000	.000	.	.000	.000	.000
	SAM_ROE2	.074	.289	.453	.000	.002	.000	.000	.000	.000	.	.000	.000

Correlations (continued)

		RED_ING_ATT	LOG_F15_FLOWN_RATIO	LIGHT	TAC-TIC2	EA2	REGEN2	RXN_LVL	MAX_LIVE_GRPS	SAM_LVL	SAM_ROE2	REC	BIG_CROW2
	REC	.137	.329	.405	.000	.000	.001	.000	.000	.000	.000	.	.000
	BIG_CROW2	.108	.167	.335	.000	.000	.001	.000	.000	.000	.000	.000	.
N	RED_ING_ATT	67	67	67	67	67	67	67	67	67	67	67	67
	LOG_F15_FLOWN_RATIO	67	67	67	67	67	67	67	67	67	67	67	67
	LIGHT	67	67	67	67	67	67	67	67	67	67	67	67
	TACTIC2	67	67	67	67	67	67	67	67	67	67	67	67
	EA2	67	67	67	67	67	67	67	67	67	67	67	67
	REGEN2	67	67	67	67	67	67	67	67	67	67	67	67
	RXN_LVL	67	67	67	67	67	67	67	67	67	67	67	67
	MAX_LIVE_GRPS	67	67	67	67	67	67	67	67	67	67	67	67
	SAM_LVL	67	67	67	67	67	67	67	67	67	67	67	67
	SAM_ROE2	67	67	67	67	67	67	67	67	67	67	67	67
	REC	67	67	67	67	67	67	67	67	67	67	67	67
	BIG_CROW2	67	67	67	67	67	67	67	67	67	67	67	67

Variables Entered/Removed (a)

Model	Variables Entered	Variables Removed	Method
1	LOG_F15_ FLOWN_RATIO	.	Forward (Criterion: Probability-of-F-to-enter <= .050)
2	EA2	.	Forward (Criterion: Probability-of-F-to-enter <= .050)
3	RXN_LVL	.	Forward (Criterion: Probability-of-F-to-enter <= .050)

a Dependent Variable: RED_ING_ATT

Model Summary (d)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.322(a)	.104	.090	.2112013	.104	7.531	1	65	.008
2	.419(b)	.175	.149	.2041876	.071	5.542	1	64	.022
3	.568(c)	.323	.291	.1864914	.148	13.722	1	63	.000

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Predictors: (Constant), LOG_F15_FLOWN_RATIO, EA2
c Predictors: (Constant), LOG_F15_FLOWN_RATIO, EA2, RXN_LVL
d Dependent Variable: RED_ING_ATT

ANOVA (d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.336	1	.336	7.531	.008(a)
	Residual	2.899	65	.045		
	Total	3.235	66			
2	Regression	.567	2	.283	6.800	.002(b)
	Residual	2.668	64	.042		
	Total	3.235	66			
3	Regression	1.044	3	.348	10.008	.000(c)
	Residual	2.191	63	.035		
	Total	3.235	66			

a Predictors: (Constant), LOG_F15_FLOWN_RATIO
b Predictors: (Constant), LOG_F15_FLOWN_RATIO, EA2
c Predictors: (Constant), LOG_F15_FLOWN_RATIO, EA2, RXN_LVL
d Dependent Variable: RED_ING_ATT

Coefficients (a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Toler-ance	VIF
1	(Constant)	.706	.028		24.927	.000	.649	.762					
	LOG_F15_ FLOWN_ RATIO	.225	.082	.322	2.744	.008	.061	.388	.322	.322	.322	1.000	1.000
2	(Constant)	.429	.121		3.552	.001	.188	.670					
	LOG_F15_ FLOWN_ RATIO	.208	.079	.298	2.618	.011	.049	.367	.322	.311	.297	.992	1.008
	EA2	.087	.037	.268	2.354	.022	.013	.162	.295	.282	.267	.992	1.008
3	(Constant)	.588	.118		4.966	.000	.351	.824					
	LOG_F15_ FLOWN_ RATIO	.193	.073	.277	2.655	.010	.048	.338	.322	.317	.275	.989	1.011
	EA2	.160	.039	.492	4.089	.000	.082	.239	.295	.458	.424	.742	1.347
	RXN_LVL	-.165	.045	-.444	-3.704	.000	-.254	-.076	-.199	-.423	-.384	.748	1.337

a Dependent Variable: RED_ING_ATT

Excluded Variables (d)

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	LIGHT	-.104(a)	-.850	.398	-.106	.920	1.087	.920
	TACTIC2	.151(a)	1.289	.202	.159	.989	1.011	.989
	EA2	.268(a)	2.354	.022	.282	.992	1.008	.992
	REGEN2	-.185(a)	-1.555	.125	-.191	.957	1.045	.957
	RXN_LVL	-.198(a)	-1.711	.092	-.209	1.000	1.000	1.000
	MAX_LIVE_GRPS	-.154(a)	-1.313	.194	-.162	.989	1.011	.989
	SAM_ROE2	-.157(a)	-1.344	.184	-.166	.995	1.005	.995
	REC	-.118(a)	-1.007	.318	-.125	.997	1.003	.997
	BIG_CROW2	-.116(a)	-.981	.330	-.122	.986	1.015	.986
2	LIGHT	-.058(b)	-.480	.633	-.060	.892	1.120	.892
	TACTIC2	-.257(b)	-1.219	.227	-.152	.288	3.471	.288
	REGEN2	-.200(b)	-1.752	.085	-.216	.954	1.048	.951
	RXN_LVL	-.444(b)	-3.704	.000	-.423	.748	1.337	.742
	MAX_LIVE_GRPS	-.465(b)	-3.628	.001	-.416	.658	1.520	.658
	SAM_ROE2	-.290(b)	-2.472	.016	-.297	.868	1.151	.866
	REC	-.330(b)	-2.640	.010	-.316	.756	1.322	.752
	BIG_CROW2	-.404(b)	-3.077	.003	-.362	.660	1.514	.660
3	LIGHT	.036(c)	.317	.752	.040	.847	1.181	.691
	TACTIC2	-.055(c)	-.273	.786	-.035	.264	3.784	.264
	REGEN2	.099(c)	.706	.483	.089	.546	1.833	.428
	MAX_LIVE_GRPS	-.207(c)	-.706	.483	-.089	.126	7.943	.126
	SAM_ROE2	.013(c)	.078	.938	.010	.421	2.375	.363
	REC	-.136(c)	-.975	.333	-.123	.550	1.817	.544
	BIG_CROW2	-.205(c)	-1.349	.182	-.169	.458	2.183	.458

a Predictors in the Model: (Constant), LOG_F15_FLOWN_RATIO
b Predictors in the Model: (Constant), LOG_F15_FLOWN_RATIO, EA2
c Predictors in the Model: (Constant), LOG_F15_FLOWN_RATIO, EA2, RXN_LVL
d Dependent Variable: RED_ING_ATT

Collinearity Diagnostics (a)

Model	Dimension	Eigen value	Condition Index	Variance Proportions			
				(Constant)	LOG_F15_ FLOWN_RATIO	EA2	RXN_LVL
1	1	1.412	1.000	.29	.29		
	2	.588	1.549	.71	.71		
2	1	2.254	1.000	.01	.07	.01	
	2	.725	1.764	.01	.93	.01	
	3	.022	10.230	.99	.00	.99	
3	1	3.180	1.000	.00	.02	.00	.00
	2	.769	2.033	.00	.97	.00	.00
	3	.031	10.210	.42	.01	.04	.89
	4	.021	12.349	.58	.00	.95	.10

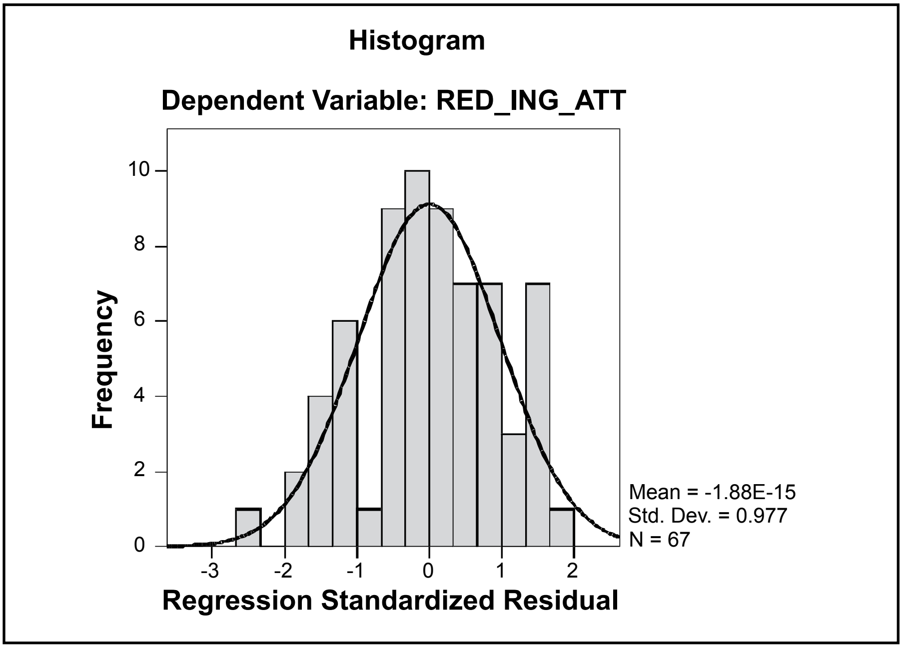
a Dependent Variable: RED_ING_ATT

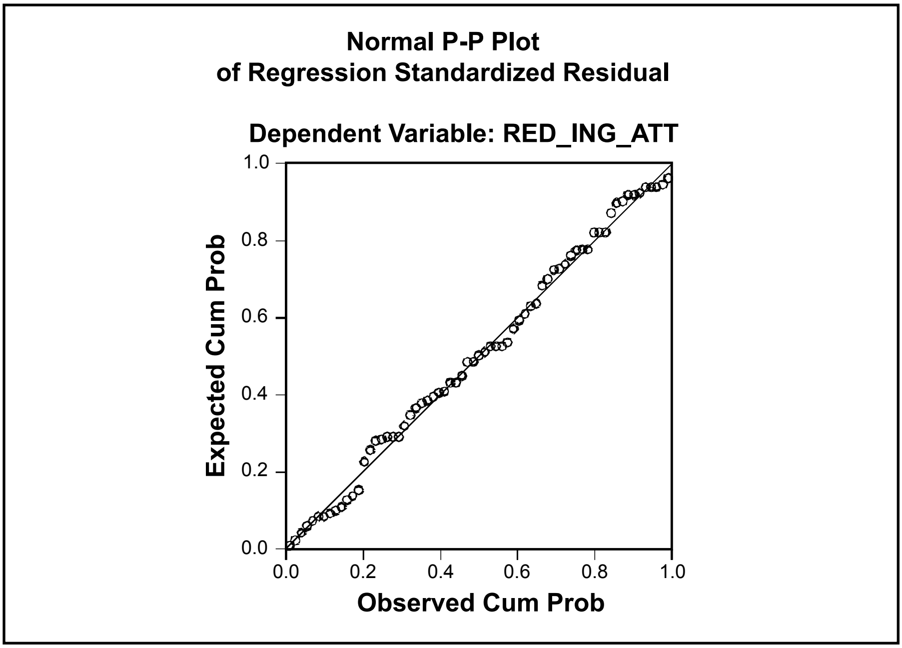
Residuals Statistics (a)

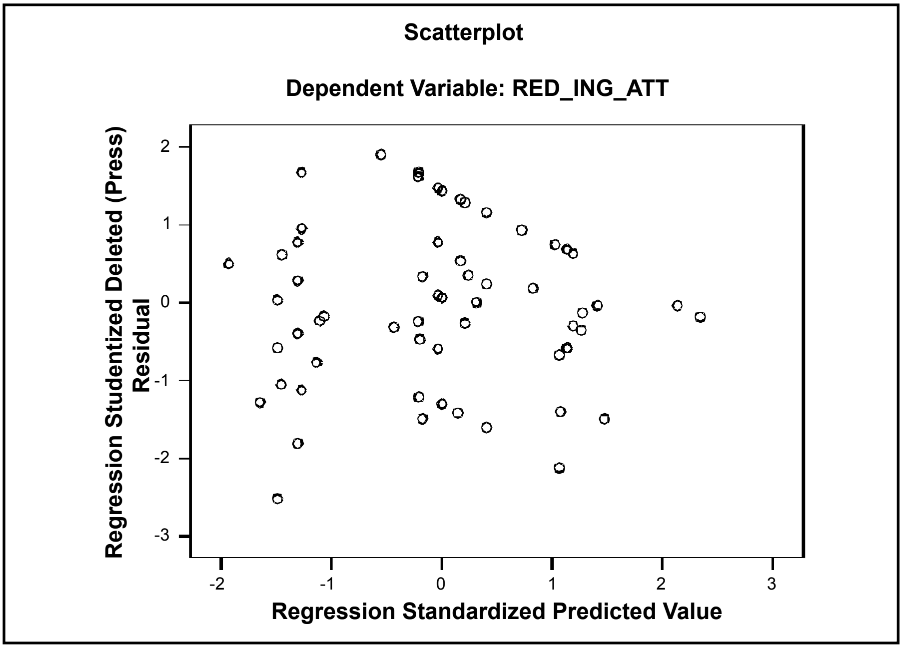
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.494902	1.032380	.737703	.1257844	67
Std. Predicted Value	-1.930	2.343	.000	1.000	67
Standard Error of Predicted Value	.027	.070	.044	.011	67
Adjusted Predicted Value	.486527	1.036057	.738585	.1280233	67
Residual	-.4393155	.3313461	.0000000	.1822037	67
Std. Residual	-2.356	1.777	.000	.977	67
Stud. Residual	-2.422	1.858	-.002	1.008	67
Deleted Residual	-.4644304	.3623375	-.0008825	.1940250	67
Stud. Deleted Residual	-2.523	1.896	-.004	1.020	67
Mahal. Distance	.363	8.380	2.955	1.981	67
Cook's Distance	.000	.092	.016	.023	67
Centered Leverage Value	.006	.127	.045	.030	67

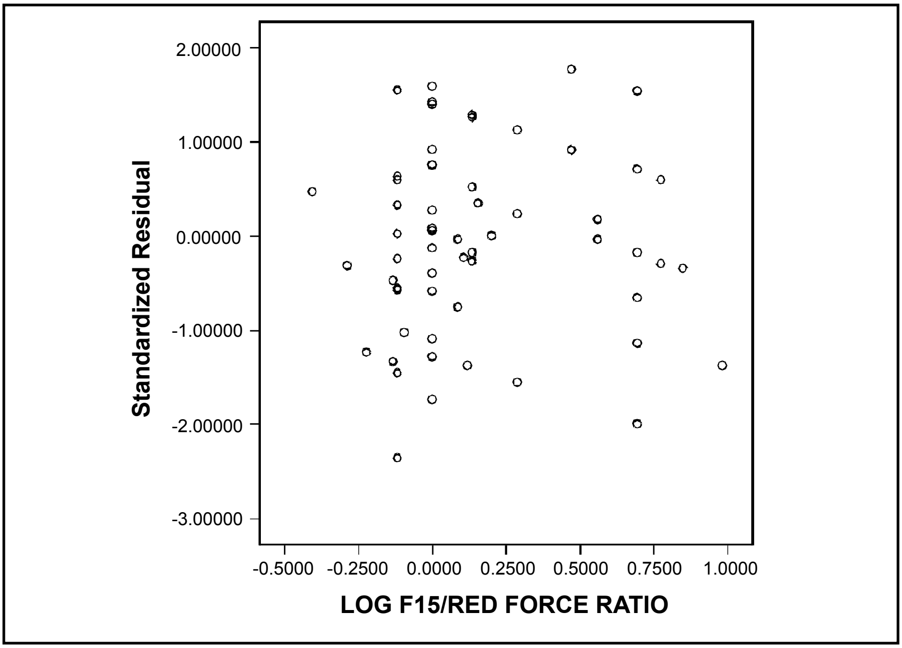
a Dependent Variable: RED_ING_ATT

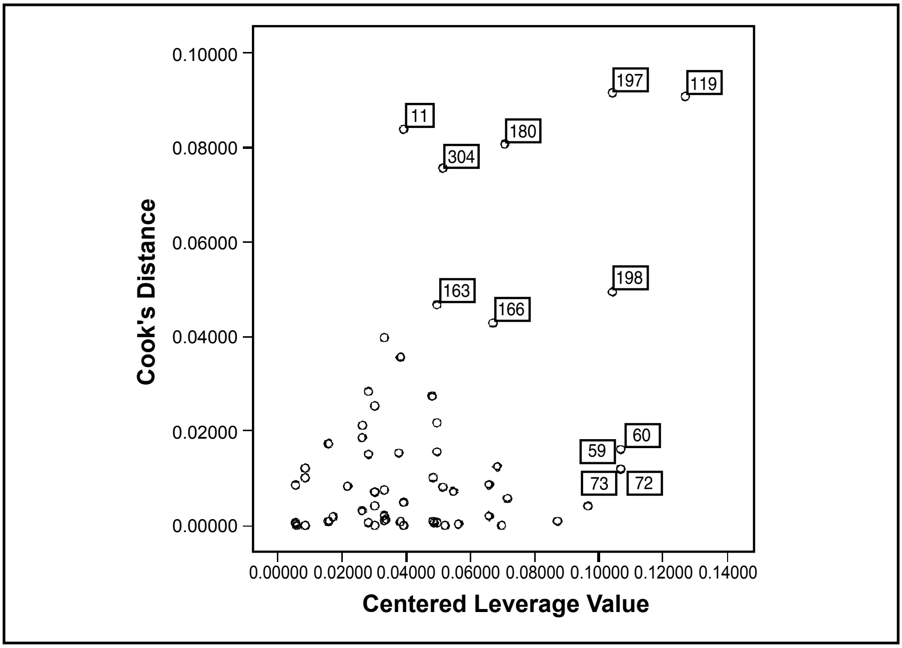
Charts


Histogram
Dependent Variable: RED_ING_ATT
Frequency
10
8
6
4
2
0
-3
-2
-1
0
1
2
Regression Standardized Residual
Mean = -1.88E-15
Std. Dev. = 0.977
N = 67


Normal P-P Plot
of Regression Standardized Residual
Dependent Variable: RED_ING_ATT
Expected Cum Prob
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Observed Cum Prob


Scatterplot
Dependent Variable: RED_ING_ATT
Regression Studentized Deleted (Press) Residual
2
1
0
-1
-2
-3
-2
-1
0
1
2
3
Regression Standardized Predicted Value


Standardized Residual
2.00000
1.00000
0.00000
-1.00000
-2.00000
-3.00000
-0.5000
-0.2500
0.0000
0.2500
0.5000
0.7500
1.0000
LOG F15/RED FORCE RATIO



Cook's Distance
0.10000
0.08000
0.06000
0.04000
0.02000
0.00000
0.00000 0.02000 0.04000 0.06000 0.08000 0.10000 0.12000 0.14000
Centered Leverage Value
197
119
11
180
304
163
198
166
60
59
73
72

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After you have read this research report, please give us your frank opinion on the contents. All comments—large or small, complimentary or caustic—will be gratefully appreciated. Mail them to the director, AFRI, 155 N. Twining St., Maxwell AFB, AL 36112-6026.

Air Superiority at Red Flag: Mass, Technology, and Winning the Next War **Locke**

Thank you for your assistance.

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